Ultrasound Sensing and Hand Gesture Recognition for Dexterous Prosthetic Devices

by

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Whilst registered as a candidate for the above degree, I have not been registered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submitted for any other academic award.
Abstract

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Traditional myoelectricity-based systems have inherent limitations and weaknesses to control dexterous prosthesis. The gap lies not in the methodologies that already extensively researched, but the means of signal extraction from the forearm. This thesis has explored and successfully tackled the practical control problems of dexterous prostheses using Sonomyography (SMG). Two hypotheses were made and supported by relevant literature to highlight the type of contraction that relevant to the amputees. The relevance of Fatigue-less Maximum Isotonic Contraction (FLMIC) phase is highlighted in SMG with experimental data. A novel wearable and portable SMG capturing system is presented with performances on a par with myoelectric methods. The Quasi-radial construction of the ultrasound transducer array allows reading A-mode signals from both anterior and posterior compartments of the forearm. The arrays comprised of transducers which are purpose designed to meet the requirements. The experiments with amputee and healthy subjects revealed that comparable gesture recognition accuracies can be achieved.

Proportional control of prosthesis is a noted problem. Since the majority of morphological changes occur in isotonic or dynamic region, the tension produced by the muscle is low. Contrary to sEMG, where it requires a significant motor unit activation, a low level muscle activation is enough to provide proportional control using sonomyography. This phenomenon is investigated in this thesis. The cross-correlation method has been employed to recognize gestures between test and training sets.

The experimental results demonstrated the ability to utilize the system in underwater without significantly compromising the performance. The experiment also demonstrated that the effectiveness of Oil based coupling medium in such conditions. In this study a novel wearable ultrasound hardware is presented with evidence to prove its comparable performances with myoelectric systems.


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Abbreviations

US  Ultra Sound
sEMG  surface Electro MyoGraphy
DSP  Digital Signal Processor
ADC  Analog to Digital Converter
CSA  Cross Sectional Area
WURMADS  Wearable Ultrasound Radial Muscle Activity Detection System
MMG  Mechano MyoGraphy
FSR  Force Sensing Resistor
NIR  Near Infra Red
SMG  SonoMyoGraphy
TX  Transmitter
RX  Receiver
FLMIC  Fatigue Less Maximum Isometric Contraction
CC  Cross Correlation
FPGA  Field Programmable Gate Array
FES  Functional Electrical Stimulation
MVC  Maximum Voluntary Contraction
PZT  Lead Zirconate Titanate
PCB  Printed Circuit Board
HMI  Human Machine Interface
Chapter 1

Introduction

In the context of machine intelligence and Human-Machine Interfaces (HMI), human gesture recognition has been a prominent domain. One of the key aspects of human gesture recognition is to facilitate a control strategy to operate dexterous prostheses.

With ever increasing upper and lower limb amputees due to medical reasons and trauma, the governments are spending a vast amount of funds to improve their quality of life. In the UK alone approximately 5-6000 amputations are carried out mostly for Peripheral Arterial Disease (PAD) related illnesses and diabetes. Other amputations are carried out due to diseases such as cancer, serious trauma to the limb by accident (or blasts) and deformity of the limb. In most instances, those who have had an amputation reported feelings such as grief and bereavement. This forces the rehabilitation and healthcare authorities to facilitate or improve prosthetic limbs at least to give them aesthetic appearance. Cosmesis is a new field of art in which making artificial limbs look life-like. This is evident in recent development of remarkably life-like robot series by Hiroshi Ishiguro of Osaka University Japan. However, even today, majority of prostheses have been fabricated primarily to restore motor function but very little emphasis on aesthetic appearance and natural usability.

In recent years, prosthetic limbs have become increasingly sophisticated and usable. There are many different variations of prosthetic limbs for upper and lower extremities. Since this study is based on human trans-radial (below elbow) amputee Human-Machine Interfaces (HMI), further references in the thesis will only be made to upper extremity prosthesis. In most cases, modern prosthetic limbs have not yet evolved to the point where they can outperform the functionality provided by biological limbs. There are many technological hurdles to overcome to satisfy some of the natural aspects of the biological limbs such as sensory feedback. Trans-radial and hand amputation accounts for approximately 10% of all amputations. Forearm or hand amputation puts the patient
to even difficult position, as they cannot perform most of the day-to-day activities. Lower extremity amputees have numerous ways to travel, by means of wheelchair, crutches etc. However upper extremity amputees continue to struggle to perform activities that involve fine control of fingers and wrist to do complex yet common activities, for an instance making a cup of coffee. Arguably, human hand is the most complex anatomical structure to restore and replace with electric prostheses as there are 20 prominent muscles in the forearm (12 and 8 in the posterior and anterior compartments respectively).

Predominantly there are two types of prosthesis, active and passive. In this thesis, presented methodologies are formulated to control hand and digital prosthesis. Active hand prostheses come in different levels of functionalities and capabilities. In addition, cost of such systems can be less appealing to many amputees and healthcare organizations. In a highly cited study conducted by (Biddiss and Chau, 2007) to determine the reasons for abandonment of upper limb prosthesis, found that state of available technology was a key factor in the areas of comfort and function. Another study on usability testing found that if the upper limb prosthesis failed to deliver the user’s needs or they likely to be abandoned (Resnik, 2011).

Invasive methods such as Intramuscular EMG (iEMG) are technically challenging and difficult to use in dexterous prostheses. Therefore this thesis only focused on non-invasive Methods. It has always been a challenge to correctly interpret the muscle activities of extrinsic muscles in the forearm rather than translating a gesture/posture to a prosthesis. Low Intensity Pulse Ultrasound (LIPUS) is a therapeutic variation of US, which is widely discussed but doesn’t fall under the context of the thesis.

1.1 Research Motivation

With the advancements of electromechanical devices, complexity of robotic prosthesis increased tremendously. Miniaturised electric motors and drive circuitries have massively influenced the ability to manufacture compact and higher degree of freedom (DOF) prosthetic hands. For an instance, Shadow Dexterous Hand (The Shadow Robot Company Ltd, England) has 20 actuated DOF. With the advances in 3D printing technologies, (Zaman), it is evident that there is an increased interest to reduce manufacturing costs and include flexibility in design. High degree of freedom prosthesis demands an efficient controller in order to acquire the full benefits of the added functionalities. Presently, almost every commercially available prosthetic hands are based on surface EMG technology with traditional threshold based on/off activation to facilitate a few basic gestures. The control problem of Active Hand Prosthesis (AHP) was predicted by (Castellini and van der Smagt, 2009) as the prosthetic hands become more complex and flexible.
Therefore actions like, twisting a door knob, grabbing a pencil, require complex digit manipulation and control strategy that goes beyond the simple on/off approach. Castellini has also pointed out the prevalent practical problems of non-invasive myoelectric signal (MES) based applications. Those notable practical problems are listed below.

- Inter-subject variability
- Arm posture and movements
- Muscle fatigue
- Electrode displacement
- Cross-talk
- Inability to operate in moist, highly humid or underwater conditions
- Being affected by electrical interferences such as FES

First two problems are common in most cases. Forearm muscle structure and sizes could differ among the subjects. In some instances, amputee subject could be a child, in which case muscular structure vastly differs from an adult. Another common problem unique for the forearm is the relative motion of the sensor position with pronation to supination. Above two problems are generally common in both myoelectric, Sonomyographical (SMG), Mechnomyography (MMG) and Near Infra-red Spectroscopy (NIRS) approaches. This problem can be addressed by using high density electrode/sensor arrays.

However muscle fatigue and electrode displacement evidently affect the myoelectric detectability. Muscle fatigue is a well studied phenomenon in which the myoelectric twitching frequency diminishes with time. The second notable problem being the electrode displacement with respect to muscle. The ideal location to place the EMG electrode is on the target muscle’s belly $l/2$ where $l$ is the muscle length. When a muscle contracts isotonically, its length reduces but asymmetrically. During the isotonic phase of the muscle contraction, length reduces and the belly of the muscle moves towards the fixed point in Lateral epicondyle. However skin surface where electrodes are attached doesn’t move with respect to the muscle, impacting the myoelectric signal reception. This relative motion could negatively impact the signal amplitude.

It is also an important point to note that sEMG vastly varies from person to person and task to task. The changes in velocity or cadence and the onset of fatigue can affect the sEMG patterns. Cross-talk is another major factor that make EMG signal interpretation difficult. According to available literature there is no fixed or proven solution for this.
Cross-talk on the hand is a well studied phenomenon that is relevant to the compartments with higher muscle densities such as forearm. Therefore the discussion of crosstalk is important to investigate its impact on dexterous prosthesis control. The debate of EMG’s ability to distinguish individual digit movements in the forearm is dubious. Ability to read deeper as well as superficial muscles in the forearm is an important factor for better dexterous prosthesis control. However the author would like to hypothesize that to interpret complex gestures, the cross-talk between deeper, superficial and neighbouring muscles could affect negatively.

Surface EMG monitoring of physiological activities in water is called Water Surface Electromyography - WaS - EMG (Panek et al., 2007). This method can be applied to dexterous prosthesis if they are manufactured to be water tight. However this technique requires special skin preparation to make the electrode contact waterproof, making it impractical in real applications where it may be used everyday. Secondly, whether it is bipolar or monopolar electrode configuration, impedance between them must be in the order of Mega Ohms to develop large enough potential difference (Day, 2000). Sweat formation under the electrodes is a common problem (Abdoli-Eramaki et al., 2012), which also contributes to crosstalk of signals between the electrodes at the skin surface. Sweat formation under both dry or wet electrodes could also affect the EMG signal characteristics. Other existing feasible methods are Mechanomyography (MMG), Near Infrared Spectroscopy (NIRS). The MMG measures the acoustics and vibrations produced by the flexing muscles. Above methods are discussed in detail in Chapter 2.

The relevant literature is limited on SMG purpose built hardware. Furthermore there is no literature on purpose built wearable hardware extracted datasets from amputee subjects.

However, to date, there are no reliable controllers based on the methods other than sEMG. SMG, on the other hand has not evolved enough to be portable and practical to tackle the stated problems. This is one of the motivations in this research to investigate the feasibility of other technologies to address the dexterous nature of modern prostheses.

1.2 Research Aim and Objectives

Initial hypotheses were made based on the current literature. Surface EMG and SMG are technically different detection mechanism. Although the results are comparable, muscle activity extractions methods are distinct. By utilizing the hardware and datasets, following theoretical questions were addressed in this thesis. Following a thorough analysis of the existing technologies Ultrasonography is chosen as the direction of research to
facilitate a control mechanism for dexterous prosthesis. Moreover two key motivation factors play a key role for this thesis research.

1.2.1 Hypothesis: 1

"Amputee muscle contraction is Isotonic with no tension"

In hand or trans-radial amputees, lengthy indolence and inactivity of the undamaged muscles result Muscle Atrophy in which the muscle volume reduces with time. However as a standard procedure, during the amputation operations, the cut tendons will be allowed to move freely without any disruptions or shortens distally (NA) (MD, 1998). This suggests that regardless of the amount of force produced, morphological changes can still take place. Physiological analysis of amputees revealed that forearm muscle contraction can mainly be isotonic. Since there is no tension in the cut tendons, the contraction speed can be higher than the healthy subjects (11 amputee subjects used in this research also demonstrated similar characteristics). However at Maximum Voluntary Contraction (MVC), 90% of them reported pain and discomfort at tetanic region. If most of the morphological changes occur during the isotonic contraction phase, it is the most relevant type of contraction for this study. Furthermore it is difficult to obtain studies that are clearly stating the impact of isotonic contractions in amputee subjects. However (Stern et al., 2001)[pp 108-109], (Widmaier et al., 2004) specifically emphasizes the difference between the two types of contractions with regards to tension. In their definition muscle tension is directly related to EMG activity. Also noted that there is a close correspondence between sEMG developed and the tension in isometric phase where muscle length is fixed. In contrast, in isotonic contractions, tension-length relationship continually changes hence resulting an non-linear relationship.
We can hypothesize that low MUAP (Muscle Unit Activation Potential) is required to reduce the fatigue and strain imposed on the muscles. Note that the objective of adopting myoelectric sensing in prosthesis control is not to evaluate muscle conditions, (relevant to the clinical, exercise and rehabilitation aspects of it) but to obtain some indication of the subjects intended gesture through the muscle activities. This is a very important point to consider in the context but rarely signified. This could be the reason behind slow evolution of dexterous prosthesis control with sEMG technology?. However the available technologies to extract forearm muscle activities require a novel hardware approach to go beyond traditional threshold based on/off methods. Therefore, it is logical to hypothesize and summarize as follows,

• Amputee muscle contraction is isotonic

• Most of the morphological changes occur at low MUAP, hence low surface EMG present

• Amputees do not need to tetanically and isometrically activate the muscles to obtain reasonable morphological changes

• Above contributes to lower muscle fatigue contrary to EMG based prosthesis control

Above points are not cited or discussed in the relevant literature, which will be considered as one of the foundations for this thesis.

1.2.2 Hypothesis: 2

"Necessity of a novel wearable ultrasound capturing hardware to facilitate dexterous prosthesis control"

A recent review on ‘peripheral machine inter-faces-going beyond traditional surface electromyography’ (Castellini et al., 2014), detailed the most recent status of ultrasound techniques and its weaknesses in the context of prosthesis control. One that related to hardware is the inability to miniaturize and having to carry the US machine with the wearer. As far as the thesis is concerned this is one of the major problems noted, that was successfully addressed with feasible solutions.

It is also evident from the conclusions of many researches in the context that technical challenges of US capturing methods, hinder further evolutions. The novel hardware presented here fills this gap by introducing a low cost and feasible solution based on
Figure 1.2: Contribution on hardware aspect of this thesis. The center indicates the gap in the context which is addressed by this thesis

'sonomography'. This term was first cited in the work of (Zheng et al., 2006). Another important notion is that the presented hardware can be used concurrently with FES (Functional Electrical Stimulation) and sEMG based systems as US is immune to electrical noises or affect myoelectric signals.

Miniaturising the hardware is the primary challenge. Commercially available US systems come in different sizes and functionalities. Wearability demands the hardware to be as small as possible. As of this writing the most compact US system commercially available is the General Electric(GE) V-Scan which costs nearly $8000. The system comes with fixed probe attached to the display base station. For research work this product is unsuitable and certainly not wearable or modifiable as some electronics could be integrated in the probe. Currently there is no US wearable system in research level or commercially that could be integrated into prostheses. Apart from the electronics in these systems, US probe or transducers are the most expensive and difficult part to engineer. There are only a few transducer manufacturers in the world but exact manufacturing procedures are secretly guarded throughout the industry, specially the compound materials. Due to inherent structural limitations, US probes are taller. Some researchers have adopted a special cradles or holder to make the probes wearable Figure. 1.3.
Chapter 1. Introduction

This thesis formulated an arguments to challenge the definition for Maximum Voluntary Contraction (MVC), which is a crude way of measuring the muscle activations (hence force). The literature related to muscle activity investigations discuss about MVC. However when critically analysed, there is no reliable approach to produce different levels of stable MVC, specially Isometrically without a real-time closed loop feedback on force. In the case of amputees, different levels of isometric contractions cannot be reliably obtained. However isotonic contractions are possible if and only if the physical length variation of the muscle is taken as the measuring parameter. In another words, 0% as the resting and 100% as the fully contracted but not necessarily representing the force. For the healthy subjects, it may be possible to use force sensors or dynamometers to set a constant load, but in the case of amputees, above methods cannot be applied. Although it may be still possible for limbs but hand amputees where the controlling muscles are located in the forearm, there is no reliable means to determine the levels of contraction. Observations were further analysed and correlated with the literature in order to explain hypotheses given above in the thesis.

1.3 Research Methodology

Primarily this comprises of two phases. The detection based on ultrasound is designed and tested in the first phase. This addresses the second research problem of lack of hardware to collect required data. The second phase utilizes the developed hardware
to collect data from both able and disable subjects. In-depth data analysis were performed with collected data from both parties. Data collection sessions were conducted with participants consent and their collaboration. Further details on subjects and ethics are given in Chapter 5. Subjects were asked to perform hand gestures that widely discussed in the literature, in both EMG and SMG. Four datasets were obtained from both able and disable subjects which are detailed in Chapter 5 with collection procedure. Template based training and test sets were segmented in order for off-line analysis. Cross-correlation and k-Nearest Neighbour algorithms were adopted to analyse the accuracy of the hardware and the algorithms. This fulfilled one of the foundations of the thesis, which is to highlight two-dimensional ultrasonography is a comparable method to determine hand gestures by observing forearm muscles. Involvement of amputees supported the hypothesis firmly. Muscle activity detection hardware is wearable, therefore it required to demonstrate comparable results.

1.4 Research Contributions

This thesis makes contributions to the problems described in Section 1.2. In addition, further observations were also documented with regards to physiology of amputees and types of muscle contractions.

The reader must consider that the primary innovation presented in the thesis as a novel hardware for dexterous prosthesis control. The remaining weight is about validating and justification of the concept using the presented hardware. It is also required be aware of the state of the art US capturing systems designed for forearm which are only available at research level. Although those systems are based on modified standard medical capturing systems. Thesis limitedly report comparisons with similar hardware approaches as there are only a few related work addressing the forearm dexterous prosthesis control.

1. A review of research on forearm muscle activity detection methods
   A comprehensive survey on myo-electric and sonomyographic methods are reviewed and critically analysed. A several methodological discrepancies of previous studies were brought to attention.

2. Wearable US muscle activity detection system
   A novel wearable US transducer array is presented with its own electronic controller. This standalone hardware is capable of recording and processing 2D US images in real-time. Limited online gesture recognition is facilitated. All the datasets utilized in the thesis are captured by this hardware arrangement.
3. **Relevance of Isotonic, Isometric and Maximum Voluntary contractions in Sonomyography**

There is a gap in the literature that failed to recognize the type of contractions prevail in amputees. This thesis argues the relevance of isotonic contraction in amputees and its relationship with electromyography and sonomyography. Experimental evidence is presented to support the fact that Isotonic contractions gives better results in sonomyography compared to sEMG with isometric contractions.

4. **Gesture recognition with able and disable subjects**

Experiments were performed to evaluate the gesture recognition accuracy with both able and disable subjects using the wearable hardware. Cross-correlation method is mainly adopted to recognize gestures using training and test templates of time-series images. Comparable results are presented.

5. **Muscle fatigue and its effects on SMG**

Muscle fatigue and sEMG degradation is an understood phenomenon. However this cannot relate to the amputees as their physiology is different to the intact counterpart. This thesis presents a new term for the type of contraction prevailed in amputees, Fatigue-Less Maximum Isometric Contraction (FLMIC). Theoretical and experimental background to justify the term also presented in the thesis.

6. **Gesture recognition in submerged conditions**

Experimental evidence is presented to demonstrate the ability to recognize gestures in underwater. There is no such research in the context to date that can recognize gestures when the sensing mechanism is submerged in water. This is a noted problem but difficult to rectify with sEMG technology.

### 1.5 Thesis Outline

Ethical approval details are given in Appendix G. Thesis outline is graphically presented in Figure. 1.4.

**Chapter 2** Provides a comprehensive survey on existing technologies to monitor forearm muscle activities. The chapter also critically disuses the weakness and pointed out several discrepancies of some studies. The author has repeated some experiments and stated the observatory remarks. A muscle contraction model for amputees is graphically presented. An argument is constructed to question how accurate to use the term Maximum Voluntary Contraction (MVC) with amputees. Instead, the term "Fatigue-Less Maximum Isotonic Contraction" (FLMIC) is proposed. This type of contraction features minimum muscle fatigue while providing a greater morphological changes. The
Chapter 1. Introduction

Chapter also provides a detailed list of studies relevant to the context of this thesis with comparison. Contents of this chapter contributed to a journal paper (Fang et al., 2015).

Chapter 3
Chapter 1. Introduction

This chapter details the methods and hardware construction of the wearable system. The unique Quasi-radial construction of the transducer array is explained with hypothesis and geometrical explanation. The transducers used in this study are custom designed for the author’s specifications and its mathematical evaluation is also provided. The frequency selection experiment details, practical problems and specially adopted hardware design considerations are also discussed. In medical range ultrasound systems with multiple channels, the norm is to utilize Field Programmable Gate Array (FPGA) based systems to meet high-speed data acquisition. However a new buffering solution is introduced to eliminate FPGAs and to implement simple DSP based architecture. This approach is not cited in other literature. Another aspect of this chapter is to evaluate the performances of the hardware to meet requires resolution. Standard procedure is followed to measure spatial resolution. For our application the lateral resolution is trivial. Work of this chapter is scheduled to be presented at IEEE International Conference on System, Man and Cybernetics, 2015 (Hettiarachchi et al., 2015).

Chapter 4

Commissioning, theoretical background and evaluation of the system is presented. Medical US systems are normally subject to extensive Quality Control (QC) tests to evaluate its spatial resolution. In this chapter the newly developed hardware underwent several test to measure A-Mode axial resolution. Lateral resolution is inapplicable to Quasi-radial method. The tests utilized water basin phantom instead of expensive models designed for medical probe evaluation. Theoretical background of US wave propagation is also presented with regards to the model utilized in the design. KLM single element transducer model is applied and simulated for the radiation and physical characteristics. Huygene principle for non-focused transducer is also investigated.

Chapter 5

A discussion and anatomical overview of the forearm is presented to construct three hypotheses and justify the introductory term "Fatigue-less Maximum Isotonic Contraction" (FLMIC). Justification is further supported by the experimental results with healthy subjects. The dataset structure and experimental protocols were given with an overview of data segmentation and stimulus guides. In this study four primary datasets were produced with both healthy and disabled subjects, DB1-4. Other datasets, which are listed, contain only the test data that doesn’t involve human subjects. Relevant data collection procedures and the sessions held are detailed. In all experiments where human subjects are involved, visual stimulus was used to synchronize and guide the gesture execution. In addition, hardware performance evaluation is done to compare the results with other similar hardware. Pearson cross-correlation (CC) is used as the
primary method to recognize template based gestures. Results from preliminary data analysis are provided using the CC method.

Chapter 6

Proportional control of prosthesis is a notable problem in myoelectric control context. Popular sEMG method is mostly work on the basis of threshold based on/off control. In this section, a model based evaluation is provided and applied to the amputee dataset to predict their contraction level against graphical and actual angular data. Furthermore, k-NN and Cross-Correlation gesture recognition algorithm is also presented.

Chapter 7

In chapter 7, results of unique experiments are presented. One of the main problems with US is having to apply a coupling medium to allow better energy transfer between the transducer and the skin interface. As an alternative option, non-drying oil is tested for its retention under simulated environmental conditions. Secondly olive oil is used as a coupling medium to recognize five gestures while the forearm is submerged in water. The results were compared with both dry and submerged condition. A slight change in recognition rate was observed when the forearms of 7 healthy subjects were submerged. In the second part of the chapter, relationship between isotonic finger force and degree of muscle deformation is investigated. In this experiment tension applied to a finger was investigated on 7 healthy subjects. Lack of studies to investigate dynamic finger flexion and applied tension, motivated this experiment with the new hardware.

Chapter 8

Overall contributions of the thesis are recaptured. The author’s vision on future of this technology and possible improvements are given with examples. It has also emphasized the importance of exploring alternative approaches for forearm muscle activity detection beyond sEMG.
Chapter 2

Literature Review: Critical Analysis

2.1 Contextual Introduction

The term ‘Sonomyography’ (SMG) is the sonographical detection of architectural changes of muscles which is first introduced by (Zheng et al., 2006). However within the context of ultrasound gesture recognition for dexterous prostheses control, a very few studies have been conducted at the time of writing that are relevant to the work presented in the thesis. In a recent research paper on peripheral machine interfaces by Castellini (Castellini et al., 2014), noted the main challenges for evolution of sonomyography as a competitor to surface EMG. The main drawback has been identified as the portability due to inability to completely miniaturize the ultrasound devices. To clarify the terminology used in this thesis, some literature uses the terms ultrasonic and ultrasound. The term ultrasonic is generally refer to non-medical applications of ultrasound.

The following diagram, Figure. 2.1, depicts only the notably relevant literature based on dexterous prosthesis control using various technologies.

The listed methods are potential candidates or already employed and proven to recognize muscle activities. For the prosthesis control, surface EMG is the prominent and well explored method. In addition mechanomyography (also called vibromyography or phonomyography) is the leading and mostly researched method in the context next to EMG. Individual topics is discussed in detail in the following sections. It is also important to stress that muscle activity detection approaches given here are confined to the human forearm.
Chapter 2. Literature Review: Critical Analysis

Figure 2.1: Available methodologies to control prosthesis and detect skeletal muscle activities

This introductory section will give the reader an insight into the current state of the art techniques, experiment methodologies that are directly relevant to this study that are based on publications. The rest of the chapter will provide a generic background literature introduction.

Table. 2.1 on page 39 lists the relevant core literature for this thesis.

2.2 State of the Art: Capturing Devices

Medical range US hardware is a complex collection of electronics. In hardware designed for skeletal muscle activity sensing, there are several fundamentally important
sub-systems collectively operating to facilitate US imaging. Modern high-end US systems are expensive and delicate piece of electronics to be handled by non-professionals. There are numerous US system manufacturers such as Toshiba (Aplio, Xario and Vi-amo series), Hitachi, Olympus, Philips to name few. They all come in different sizes, capabilities and portability. As for the US semiconductor vendors, Texas Instruments, Supertex (Microchip), Maxim, Freescale are the most trusted and well supported.

2.2.1 Methods and Developments

Functionally US systems are similar to radar or sonar systems (Brunner, 2002) that work at GHz and KHz range respectively. A little over a decade ago, US systems were bulky, cumbersome and technologically very complex to maintain. With the advancements in semiconductors and miniaturised electronic components such as Surface Mount Devices (SMD) and low cost processors, systems became more compact, efficient and portable. These systems are complex due to its higher operating frequencies (>1MHz). Managing US Radio Frequency (RF) signals to execute scan cycle and capture the echoes require perfect synchronisation and high speed control faculties. The followings are the basic building blocks of a US scanner (Ali et al., 2008) (Brunner, 2002).

- Beam-former - this module generates the US pulses to be transmitted and feed to each transducer element in the array with time delays ($t_d$) to focus the collective US wave fronts to an area of interest (AOI).

- Transmit/Receive switch - An analog switch that mainly controlled by the FPGA, to change the mode of each transducer in the array. It changes from transmit to receive immediately after a burst of pulses were being transmitted. The Low Voltage (LV) echo signal is then directed to the amplifying circuits.

- Low Noise and variable gain amplifier (LNA) (VGA)

- Analog to Digital Converter (ADC) - Generally high speed ADCs are used with sampling rates above 10MSPS.

- Time Gain Control (TGC) - application of variable gain to the amplifier depending the depth

- Back-end processing - In this stage captured echoes are processed according to the selected settings by the user. User interfaces and displays are also handled by this section.
There are numerous US hardware architectures were presented over the past decade or so. In each case, the systems are constructed with the above listed basic building blocks. Effectiveness of each section is depending on the control software and the methods adopted. Apart from Medical range US, Non-Destructive Testing (NDT) is also adopting the same electronics architecture in a smaller scale. Because in US based NDT, only a single transducer element is used to inspect materials, joints etc. (Mateos et al., 2007), (Fritsch and Camacho, 2007). This simplifies the electronic hardware requirement to a certain extend making it portable. A generic single channel construction of medical range US is briefly explained in a recent work by (Li et al., 2014a), that explains the concept of A-mode receiving.

Context wise the work of (Dusa et al., 2014) is the closest to the hardware construction methods presented in this thesis (WURMADS). They have developed an eight-channel system for medical research purposes with the features of standard US system. However, majority electronics are based on, off-the-shelf modules that are readily available for US applications such as Texas Instrument US development Kits-AFE5809 and Spartan 3E FPGE development kit. Due to the ease of utilizing readily available development kits, their effort lies mainly in the software development rather than a novel hardware platform. The system is not wearable or customisable to be integrated in prosthesis and uses a FPGA. The fundamental problem with the use of off-the-shelf development kits is inability adopt easily to facilitate portable prosthesis control. If one needed to design such system, it takes a lot of experience and patience, which is not the most appealing to some research groups.

The objective of any improvements leads to enhanced spatial resolution of the images (Ali et al., 2002). In most instances, researchers focus on software methods based improvements rather than hardware such as Artificial Neural Network (ANN). Contrast to noise ratio (CNR) is another parameter that used to evaluate the spatial resolution of images captured by hardware. (duck Kim et al., 2012) have presented a hardware and compared the spatial resolution between conventional receive dynamic focusing and pseudo-dynamic focusing method. In pseudo-dynamic focusing, scanning depth is divided into number of zones in which each zone has its own delay values for focusing. The delay values are predefined and stored in a Look Up Table (LUT) to ease the complexity of the process. In conventional receive dynamic focusing, the delay values are assigned to each focusing zone. However, pseudo-dynamic focusing demonstrated negligible degradation of lateral resolution. (<0.2mm). Their hardware construction is battery powered and portable, although the wearability is questionable. Spartan-3 FPGA (Xilinx Inc.) controls the US beam-forming and Samsung S3C6410 mobile processor (Samsung Group, Suwon, Korea) running Linux at 667 MHz serves as a system controller and facilitates UI related functions.

Generally transmit waveforms are produced by FPAGAs in US systems. FPGA’s ability to
parallel processing with pipeline implementation (Levesque and Sawan, 2010) is greatly beneficial in order to generate a large number of parallel signals simultaneously. (Assef et al., 2012), (Li et al., 2014a). This is a notable drawback in DSP/Microcontroller based approaches. However, with the increased complexity of the software architecture, FPGA lags in terms of efficiency, as it requires dedicated logic blocks, which are not shareable by other parts of the software. This inevitably demands a larger and powerful FPGA solutions.

Apart from beam-forming and echo capturing, a significant processing is required for the cartesian coordinate evaluation and display image construction. In focussed beam systems, this process is intricate. A wireless back-end and a remote display unit (RDU) can share some of the workload between each other (Levesque and Sawan, 2010). In his approach, Video Graphics Controller is remotely located and is connected to the back-end wirelessly with the same data throughput. Design wise, the Analog Pre-processing Unit (PPU) is similar to the WURMADS analog front-end architecture. In his experimental system, a 5MHz mechanized scan probe that produces 90 degree sector image was used, thus, this is a different approach to the WURMADS’s. This FPGA based system has reported enhanced lateral and axial resolution by 25% and 33% respectively. Beam-forming methods constitute a great amount of literature related to hardware improvements. In phased array transducers, beam forming is crucial in order to focus the beam to a targeted region. (Dusa et al., 2014), (Hua, 2010), (Ali et al., 2008), (Assef et al., 2012). For applications with linear transducer arrays above >20MHz, (Hu et al., 2006) has proposed a FPGA based approach that can produce delays as small as 2nS using fractional delay filters.

Image interpolation - US image interpolation is widely used in modern US systems in order to smoothen the image to reduce graininess. In 2D imaging (Levesque and Sawan, 2010) 1D (X-axis) linear nearest neighbour interpolation is used. This is also employed in 3D US imaging between the frames.

2.2.2 Critical Analysis

A recent study conducted by (Huang et al., 2014) demonstrated the use of a piezoelectric PVDF transducer to evaluate the displacement of Abductor Pollicis Brevis and Flexor Carpi Radialis muscles when Peripheral Nerve Stimulation (PNS) is applied. US (RF) signal variations were recorded to estimate the degree of muscle deformation at different stimulant currents. However, the study lacks technical details, such as the targeted transducer frequency range. The author would like to question the measurements made by 20mmx20mm transducer on a comparatively smaller muscle tissue in the palm. From previous experimental experience, the author would like to suggest that the readings
could be the echo reflected by the bone (Thumb metacarpal) instead of echoes generated by muscles/boundaries. Such larger surface area transducer could not produce finer details as the beam cannot be focussed properly, hence the noise can be prominent. However PVDF based transducer is successfully used in another study (Lanata et al., 2006) as a wearable cardiac monitoring system. This application may be feasible because heart muscle covers a large area and the motions are significant during pulsating, which is detectable even with low resolution. In another instance, FPGA implementation of US power meter based on the PCDF sensor proposed by (Risman et al., 2014).

It is also evident that none of the researchers have developed their own hardware solution for gesture recognition purposes in the context. It is also evident that the all US hardware utilizes FPGA processors for the beam-forming stages and received signal reconstruction. The author considers this is primarily due to the difficulty in designing and testing of such highly complex and sensitive electronic systems.

### 2.3 Dexterous Prosthesis Control Methods

This section describes the present methodologies that currently using or potentially feasible to control dexterous prostheses. In spite of the tremendous advances achieved in the developments of dexterous anthropomorphic hand prostheses, there are no adequate controllers to provide natural and efficient usability to the amputees. This has pointed out by several studies due to inability to deliver requires expectations in prosthesis control. In a study conducted by (Biddiss and Chau, 2007) to investigate the reasons for the abandonment of prosthesis concluded that further research should focus on the development of more functional and comfortable prosthesis. In addition, it states that prosthesis rejecters were significantly less satisfied with appearance, comfort, function, ease of control, reliability and cost. The costs however are getting very competitive nowadays, with the improvements in technologies.

#### 2.3.1 Ultrasound/Ultrasonography/Sonomyography (US/SMG)

The prospect of using ultrasound (US) in forearm gesture recognition, greatly inspired this thesis. A well-established method that extensively used to visualize internal morphology of living beings has a great potential to detect muscle activities to control dexterous prostheses. Specially in the forearm where 20 muscles are packed in order to carry out various hand gestures require a method beyond myoelectric based approaches to recognize each and every movements accurately. A recent work of (Chen et al., 2011a)
revealed that A-mode multi-dimensional sonomyographical signal can be used to measure joint angle during wrist extension/flexion and control prosthesis. This is also one of few studies highlighting the usability of SMG to control prosthesis. As stated earlier, topics on US prosthesis control haven’t been widely explored and only a few (less than 10) research groups have done notable contributions in this regards. After analysing their work in detail, they can be grouped to highlight (Table. 2.1 on page 39) their common experimental set up and theme. Compared to traditional probe based methods, work of (Tsutsui et al., 2007b), (Tsutsui et al., 2007a) took a different approach using lower 200KHz US frequencies. A pair of receiving transducers with a transmitter (as a single unit) mounted on triceps and biceps of upper forearm. Echoes from 300mS bursts were collected from two receivers. By employing the Test Feature Classifier (TFC) they achieved 0.74 torque recognition accuracy and 0.82 angle recognition accuracy.

Critical Analysis: Experimental set up of the above research is highly questionable due to following listed reasons.

- Window length: The paper states that the sampling rate is 20MHz for 300uS that gives 6000 data points. However this calculation is flawed as to obtain 6000 points, the window must be 30uS. Since they have mentioned 300uS window multiple times (and six 50uS intervals) this mistake seems to be intentional.

- Time of flight: If speed of sound in soft-tissue is considered as 1540m/s, 300uS window will result a scanning depth of 0.462m ÷ 2 = 0.231m(23cm). It is difficult to assume that biceps or triceps are 23cm in thickness in upper forearm.

- Resolution: Based on the author’s experience, 200KHz is too low to detect muscle boundaries with usable resolution. At 200KHz the resolution is 7.7mm, compared to WURMADS 0.03mm at 5MHz. Therefore the pulses can easily pass through the boundaries without being affected significantly and echogenically. The significant echo would be resulted by the bone. There is no available literature to support that such low frequency is usable in detecting muscle boundaries.

Their approach utilized 1D single element transducers of very low frequency. In another study by the same researcher,(Tsutsui et al., 2005) a new signal processing method was proposed using a Ultrasound Muscle activity Sensor (UMS). In their experiment two transmitters and receivers were placed to monitor activity of quadriceps femoris muscle and biceps femoris muscle with the intention of estimating the knee joint torque. In the set up, a single transmitter is used to emit a pulse and two receivers on the adjacent side to receive it, which is also called as duplex mode (Simplex mode only utilize a single receiver). Contrary to echo ranging, this study collected time of flight,
voltage amplitude and rectified integrated value of the received signal as features. With Neural Network (NN) approach they analysed correlation coefficients between actual and estimated joint torques at three different angle settings ($30^0$, $60^0$ and $90^0$). With duplex mode that prioritised in this paper, they achieved 0.999 of correlation whereas simplex mode achieved 0.987, indicating a slight improvement with duplex mode.

In (Tanaka et al., 2003), a wearable ultrasound sensor disk to be worn on upper arm biceps introduced. Similar to the work of (Tsutsui et al., 2005), time of flight was measured. Their hypothesis was based on the time of flight varies with the change in elasticity and density of muscles (2.1).

$$ V = \sqrt{\frac{K}{\rho}} $$

where $V$ is the US transmission speed and $K$ and $\rho$ are the elasticity and density respectively. They hypothesized that the muscle activity causes $K$ and $\rho$ to vary, therefore, it is expected to estimate the muscle force. Similar to the previous studies 200KHz US was used and the time of flight was measured by a counter running at 625KHz in the first prototype. However they improved the hardware by increasing pulse voltage and importantly the counter clock to 20MHz. The transducers were integrated in a wearable fabric cuff that worn around the upper arm. A muscle stiffness sensor measured the pressure exerted on it by an integrated strain gauge. The experiment measured normalized received pulse (time of flight) that also affected by dispersion and the elbow joint angle. It was repeated for different joint angle values from 0 to 100% of force upward (Isometric contraction). Their experimental set up is depicted in Figure. 2.2.

\begin{figure}[h]
\centering
\includegraphics[width=0.4\textwidth]{us_transducer_setup.png}
\caption{US transducer set up for the experiment carried out by (Tanaka et al., 2003)}
\end{figure}
Chapter 2. Literature Review: Critical Analysis

The results suggest that, for a given angle, with the increment of force, there is a decrement in the received pulse. (It is unclear whether the normalized received pulse is actually the time of flight in counts). It should be noted that (Tanaka et al., 2003) is the earliest literature available with regards to wearable ultrasound based muscle activity detection in upper limb.

Critical Analysis: Above experiment is questionable and contradicts the assumptions made by the author who repeated the experiment with similar set up. However it is a valid assumption to suggest that the US speed varies due to muscle and density changes (2.1). The author repeated an experiment with higher 1MHz US frequency to measure the time of flight variation due to muscle activities. In one test, the distance between the transmitting and receiving transducers kept constant (by mounting the transducers on callipers) and the second test allowed it to move with skin. Also note that there is no available literature stating the variation of sound velocity in activated and relaxed muscles, other than a generic acoustic velocities which is normally considered as 1540m/s (Hedrick et al., 2005). The author’s experimental results suggested that there is no detectable velocity variation due to biceps concentric contraction as long as the distance it travels remained constant. The second test revealed that there is a significant change in time of flight if the transducers are mounted on a wearable materials. This occurred due to the distance variation between the transducers. However the significant difference with regards to the experimental set up is, the author performed isotonic concentric elbow contractions with time of flight measurements made at 0, 10, 20,...100% contraction levels of the elbow joint.

The results presented in Figure. 2.3 contradicts the findings in (Tanaka et al., 2003). If the distance between the transmitter and the receiver is fixed, the TOF (Time of Flight) remained stable. However, when the transducers were worn over the biceps, TOF increased proportionally, contradicting the inversely proportional nature with the increase of muscle force (Tanaka et al., 2003).

As a conclusion, it is difficult to agree to the fact that received pulse’s TOF changed due the muscle density changes as stated in their paper. The density change of the muscle during contraction is negligible, therefore it cannot be detected by counter based TOF capturing approach. However, the TOF variation is possibly caused by the very small movements of the transducers when the cross sectional area (CSA) of the biceps changed during isometric contraction. This is highly probable if the transducers were integrated in a fabric based cuff which can easily expand respect to each other. This is also evident in the isotonic contraction results (Worn graph of Figure. 2.3). Although the inverse nature of TOF change with force in (Tanaka et al., 2003) can be due to the location it was mounted. It is also questionable that isometric contraction can possibly change
the density, whereas isotonic could make an impact, because during concentric contractions, CSA increases, hence impacting the density slightly. This concluding statement is justified by the results obtained by the author (Figure 2.3).

As the original presenter of the term sonomyography (SMG), (Zheng et al., 2006) did a comprehensive study to investigate dimensional changes and control. He carried out the experiments with six intact and three amputees subjects. In both cases, a selected window that covers the muscle boundaries were tracked during a three cycles of wrist extension - contraction. The timing was guided by audible beats of a metronome (30 beats/min). The windows were 2D cross-correlated to acquire the shift. The results indicated a good linear relation between the actual angle and the percentage muscle deformation ($R^2 = 0.876\pm0.042$). This has been proven with three amputees subjects as well.
In another study (Huang et al., 2007), joint angle of the wrist has been evaluated by tracking the features in a window of B-mode ultrasound images. Then compared the results with sEMG. The results showed average correlation coefficient for regressions between muscle deformation and joint angle and SMG RMS and joint angle as 0.967 and 0.956 respectively. This suggests that there is a strong correlation between muscle deformation and sEMG.

Sonomyographic techniques are used not only with upper extremity limbs. Work of (Chen et al., 2011b) and (Chen et al., 2014) examined its application on rectus femoris (RF) muscle during isometric contraction. Polynomial regression analysis was used to find the EMG/MMG/SMG-to-torque relationships and the regression coefficients of EMG, MMG, and SMG. In addition, the effect of contraction speed on SMG, EMG, MMG-to-torque relationships were tested by pair-wise comparisons of the mean relationship curves at different speeds for EMG, MMG and SMG.

A recent study (Sikdar et al., 2014) based on healthy subjects and standard medical range probe, robustly classified individual digit movements with 98% accuracy with K-Nearest Neighbour algorithm. Emanuel Richard Zarka (Brown) has conducted a notable research by extracting features from B-Mode ultrasound images to predict finger movements. Jun Shi (Shi et al., 2010b) optical flow algorithm is employed to track five-finger flexions on US images obtained by standard probes. They have qualitatively revealed the varying optical flow patterns and deformation features can be used to classify different finger flexions. Tracking of selected prominent echo regions in the B-mode images (Sikdar et al., 2014) can be employed to evaluate the relationship between wrist extension angle and the percentage muscle deformation in the forearm with both healthy and amputee subjects. Morphological changes and linear correlation was 0.876±0.042. However, with amputees, the transient muscle deformation was not smooth, we also found evidence to support this during the training sessions with amputees. Ultrasound is also proven to be successful in identifying muscle volume changes and calibration conjunction with MRI (Fukumoto et al., 2009) using a 5MHz probe.

In two separate studies, (Ni et al., 2012) and (Guoa et al., 2010) discuss the relationship of CSA change and torque in isometric contractions along with MMG and EMG measurements. Both studies observed a decrease in muscle CSA with increase of torque (MVC), 7.25% RF muscle CSA reduction in the study of (Guoa et al., 2010). (Delaney et al., 2010) discusses the muscle CSA change during isometric contraction of RF muscle.

Figure 2.4, reveals the thickness of the RF muscle increased by 11.4% whereas width decreased by 25.9%. Although this study is based on the RF muscle, dynamics are applicable to forearm muscles (flexers) as well. However with amputees subjects it is challenging to quantify the level of force/torque. With regards to the context of the
Figure 2.4: Muscle boundary changes with different levels of MVC. The image is taken from (Delaney et al., 2010) for explanatory purpose. The author bears no copyright for the image.

thesis, M-mode US signals from each transducer presents only the change in thickness of muscles in the AOI. Although, it may be difficult to recognize inner or outer muscle boundaries in A-mode, unless M-mode features are analysed.

Following the revision of numerous literatures on the relationship between CSA and torque/force in isometric contractions, the following argument is constructed. This brings several points for consideration with regards to the methodological practicality with amputees if the end result is to control dexterous prostheses.

2.3.2 Critical Analysis: CSA Change With Isometric Contractions

Studies focused on controllers for robotic prostheses, must be based on isotonic contractions rather than isometric. As noted in Chapter 5 on amputees physiological nature, the test group could not perform isometric contractions and that is true for other trans-radial amputees as well. Therefore none of the prostheses control strategies cannot rely upon the results obtained by isometric contractions. Results published by numerous studies are based on healthy subjects with isometric contractions in order to investigate the relationship between CSA, force and myoelectric characteristics.

Isotonic contractions are dynamic contraction in which the force generated by the muscle is greater than the load, whereas isometric is static in which the muscle length stays constant as the load is greater than the force. Therefore it is not difficult to conceive of our majority everyday movements are isotonic, other than holding something like a glass of water. Isometric however widely considered beneficial for body-building exercises and rehabilitation, which is out of the scope of this research.
In trans-radial amputees, isometric contraction may be possible at the peak of the isometric contraction phase (Gailey et al., 1992). By then, most of the morphological changes have taken place, and further contraction to reach isometric phase, which is non-linear, only stresses the muscles.

Hodges (Hodges et al., 2003), studied the muscle architectural changes (pennation angles, fascicle lengths, and muscle thickness) during the contraction of several muscles (tibialis anterior, biceps brachii, brachialis, transvers abdominis, obliquus internus abdominis, and obliquus externus abdominis). Force was represented indirectly by EMG recordings from the various muscles. They found that majority architectural change was observed up to 30% MVC, with muscle thicknesses increasing and changing little thereafter.

Amputees cannot perform isotonic or isometric contractions at different resistive torques as there is no means of applying the resistance. However they can comfortably perform isotonic contractions. This raises the question with regards to the validity of the numerous studies done to investigate sEMG for prosthesis control with intact subjects.

With above hypothesis, different phases can be presented for muscle contractions of amputees. In Figure 2.5, muscle deformation and force of trans-radial amputees is shown.

![Figure 2.5: Proposed graphical model for amputees](imageURL)
This graph is based on the observations made by the author and the theoretical facts regarding muscle contractions. The model is further interrogated in chapter 5.

Castellini and his team are a prominent research group in forearm’s ultrasonographic gesture recognition regime. Ultrasound images taken at the wrist joint revealed a linear relationship for finger flexions and thumb rotation in two of his studies (Castellini and Passig, 2011) (Castellini et al., 2012). Using a computationally light-weight linear model a good recognition rates were achieved. Anatomically human wrist contains only a few muscles, majority of B-mode image changes occur due to tendons movements. Therefore, this linear relationship is particularly valid for finger and tendon movements. Finger controlling muscles are mainly located on ventral and dorsal sides of the upper forearm as flexor and extensor muscles. It is observed that residue sEMG activities were present in trans-radial amputees even after decades (Castellini and van der Smagt, 2009; Sebelius et al., 2005; Cipriani et al., 2011). This suggests that using US imaging, which produces greater details than sEMG, it is possible to investigate the activities more precisely.

(Castellini and Gonzalez, 2013) and (Gonzlez and ClaudioCastellini, 2013) studied the finger tip force by analysing B-Mode US images. Both experiments have been carried out by analysing the images taken on the ventral side of intact forearms. A comprehensive study by (Gonzlez and ClaudioCastellini, 2013) managed to predict the finger force values, spanning a range of about 20N per finger with average errors in the range of 10-15%. The results are based on ON/OFF and graded ‘isometric’ contractions (Although they haven’t mentioned it). This suggests that the muscle lengths were sparsely changed even at 20N of force, but good enough for the recognition. On one of the graphs depicted in both of their studies, considerable discrepancies are evident between actual and observed finger tip forces (for MVC). This indicates that in isometric contractions, levels between 0% - 100% MVC can be difficult to precisely establish by the subject and cannot considered as accurate from the experiment’s point of view. Therefore it is also logical to conclude that isometric contractions based force estimations could be affected by uncertainties and errors which is worth further investigating.

Texture and features based analysis are the two methods that often adopted in sonomyography (Zhou and ping Zheng, 2012). Window based cross-correlation (CC) and optical flow tracking of the area of interest is widely employed. Feature based analysis extract geometrical features such as muscle boundaries directly from the images, that are highly echogenic. They used Revoted Hough Transform (RVHT) and Revoted Radon Transform to extract the boundary lines. Kinematic features of sEMG and SMG showed very closed correlation. The methods used in this thesis consist of both feature and texture based analysis.
When it comes to envelope extraction of A-mode US signal and other signal processing applications, Hilbert transformation (Qiu et al., 2014b) is widely utilized. Guo and his team have performed a study with a single element standalone transducer (Guo et al., 2008a,b, 2009a). They measured the muscle deformation and root mean square (rms) signal against wrist extension angle. They have observed a linear relationship.

It is also feasible to construct a relationship between sEMG and ultrasound, previously mentioned studies present clear evidence for this. Furthermore, the hardware we have presented here can also be used in conjunction with sEMG capturing systems. A research (Guo et al., 2008b) has clearly highlighted the linear relationship of muscle contraction using A-mode 1D single element US to detect feature variations. Castellini (Castellini and Gonzalez, 2013) concludes the presence of a linear relationship between finger forces and the ultrasound images. Using ultrasonography it is much easier to identify activities in larger yet simple muscular structures found in legs. A wearable and flexible PVDF piezoelectric polymer film (AlMohimeed et al., 2013) is proven to be successful in recognizing muscle deformations at 1.8 and 2.2MHz. Pulsed-echo and through-transmission methods were used in their experiment. However similar experiments we carried out using piezoelectric ceramic failed to produce satisfactory results without proper backing material and matching layers. This is due to the extensive ringing of the ceramic immediately after the excitation (Hedrick et al., 2005).

Note that above-mentioned researches are primarily based on standard US probes, base stations (with B-mode images) in which the bulkiness hinders portability and wearability on the forearm to control robotic prosthetic hands. To the best of our knowledge, we are the first to introduce a new custom designed portable base station, US transducers and wearable US band that could potentially resolve the inevitable limitation issues that previous researches have faced. In the context of hardware development we couldn’t find any notable researches that are focused on the forearm and wearability. Therefore, we consider our research remains the pioneering in terms of recognising hand gestures with a purpose built novel hardware.

2.3.3 Mechanomyography (MMG)

MMG is a muscle activity detection method introduced decades ago as an alternative to the Electromyography. It mainly focuses on detecting the changes of mechanical properties of the muscle or a group of muscles under investigation. MMG is also called in some literatures as Phonomyography, Vibromyography and Soundmyography. The phenomenon of muscle sound or vibration was first observed by an Italian scientist
Francesco Maria Grimaldi. (Circa 1665). The vibration range of MMG is 5-50Hz with no significant frequency components beyond 100Hz. In recent times, the method has been further improved with the advances in electronics and related components. MMG mainly utilizes microphone and an accelerometer to capture muscle acoustic and vibratory features during contractions. This technique is sparsely discussed in the context of prosthesis control.

(Silva et al., 2003) pointed out that the soft silicone socket below-elbow prostheses are favoured due to the advantages such as comfort and functionality in a study of multi-sensory data fusion for prosthesis control. However, wire breaking issues associated with sEMG integration was problematic in electrically powered below elbow prosthesis. An embedded microphone and an accelerometer in silicone socket were used as the sensor in this study. A binary control strategy based on the Root Mean Square (RMS) value was adopted in the above study with 95% and 86% accuracies were recorded in the detection of contraction signals from the wrist extensor and flexor.

In another study by the same group (Silva et al., 2004), three MMG sensors were arranged radially inside the silicone sleeve with 120 degrees equally spaced (equiangular sensor distribution) as the detection mechanism. In their experiment, sEMG data was also recorded for a comparison. In both studies, they have primarily executed only a two prominent gestures, wrist flexion and extension. Keeping the EMG signal threshold (0.05V) as the datum to define the target window, RMS-based classification (RBC) and cross-validation have produced around 70% classification accuracy for two amputee subjects. They have also noted that the MMG is comparable and may exceed EMG functionally and feasible to use in current EMG based prosthesis concurrently.

Contractile muscle force in the Brachioradialis is quantified (Cole et al., 2006) by employing the Vibromyography (VMG) of 24 healthy subjects. A capacitive accelerometer was used in the study as the sensory mechanism. The data was recorded for 0 - 100% MVC at different force levels (4.45N to maximum sustained load). VMG signals were decomposed using wavelet packet analysis techniques. Their experimental results revealed a direct correlation between weighted MMG(VMG), RMS response and Force. It also suggests that wavelet components were sufficient to accurately predict muscle force ($R^2 = 0.984$). In the context of MMG, the fundamental measuring parameter is the RMS amplitude value of the signal. Unlike sEMG signals, limited frequency bandwidth (5-50Hz) carries comparatively less frequency and phase components for processing. (Lei et al., 2011) proposed frequency variance as a new measuring parameter to construct a MMG torque estimator. Seven subjects based experiment adopted two-layer neural network as the modelling algorithm with MEMS based accelerometer as the sensor. The experiment revealed that the frequency variance decreased under incremental voluntary
contractions. The predicted torque was reasonably matched with the actual torque measure by the dynamo-meter.

**Critical Analysis:** In order to produce significant measurable signal by microphone or accelerometer, the subject must produce considerable contractions reaching the tetanic phase. The author also sees environmental noise and movement artefacts (noise) filtration is an essential yet underdeveloped area in MMG. This could impose undesirable error to the force prediction and estimations.

### 2.3.4 Electromyography (EMG)

Fundamentally there are two types of Electromyography, Clinical and Kinesiological. Clinical (sometimes called diagnostic), typically done by physiologists and neurologists to study motor unit characteristics such as action potentials, duration and amplitude. Kinesiological EMG is the commonly found method in literature that analyse movement related EMG. In a typical skeletal muscle there are multiple motor units. Each motor unit consists of 3-2000 muscle fibres. Muscles that control fine movements such as fingers, hand gestures, typically contain less than 10 fibres per motor unit. Larger muscles such as biceps could contain 100-1000 fibres per motor unit (MU). In this chapter almost every referred study is based on Kinesiological EMG, to analyse features and acts as a part of a control system. In Kinesiological EMG, two main types of electrodes, surface and fine wire, are being used. The fine wire method is invasive and uses a needle inserted into the belly of the muscle. This method is neither practical in dexterous prostheses control nor discussed further in the thesis. The surface electrodes can be divided into two categories;

- **Active**
  Active electrode consists of in-built amplifiers and filters that provide better signal to noise ration (SNR). These electrodes are often dry hence no coupling or skin preparation required. For example Delsys Trigno is an active wireless electrode solution.

- **Passive**
  These are the conventional electrodes with amplifiers located remotely, which causes reduced SNR and highly susceptible for motion/wire motion artefacts.

In dexterous prosthesis control, myoelectric methods are in the forefront. Commercially, all the available robotic prosthesis are based on surface EMG technology. Bionic [RSLSteeper](UK), TouchBionics (Scotland), Ottobock’s Michelangelo hand, 3D
Printed 'Open Hand Project’ (UK) are examples for commercially available prosthesis which are all based on sEMG control strategy. The Smart Hand, (Cipriani et al., 2011) is another research level 16DOF self-contained trans-radial robotic hand for neuro-engineering studies. (Micera et al., 2010) reviewed the available myoelectric methodologies including sEMG, intramuscular EMG (iEMG) and electroneurographic (ENG) signals. Neural prosthesis is a recent and rapidly progressing development that uses electrical impulses of nerves that may be implanted next to the targeted nerve (Ju et al., 2002). iEMG is an invasive method that uses needles to extract electrical impulses from the muscles (Micera et al., 2010). This method is only limited to clinical administrations and impractical in prosthesis control. It also requires ultrasound based guidance during the needle implantation (Micera et al., 2010).

Within the context of sEMG, Targeted Muscle Reinnervation (TMR) is an interesting concept, which is a surgical method that residual nerves in the arm are surgically transferred to alternative residual muscles that are no longer bio-mechanically functional. Following this process, sEMG can be extracted from those muscles to control prostheses. However, this procedure could be expensive and limited due to several factors such as available nerves, muscles and accessibility.

Myoelectric self-contained prostheses were used as early as 80s on amputees with limited electronics capabilities (PHILIPSON and SORBYE, 1981). Regardless of the maturity of the techniques, nowadays, innovations lie mainly in the recognition methodologies rather than hardware. (Matrone et al., 2012) used four electrode based system to control multi-fingered robotic prosthesis. To the best of knowledge of the author, the novelty is mainly lies in the method which is Principle Component Analysis (PCA). It is evident that majority of the researches are primarily focussed on implementing and improving classification methods to reduce errors.

sEMG signals are naturally highly susceptible to noise. In multi-electrode array systems, a faulty electrode or lift off from the skin can greatly diminish the recognition rate by adding disturbances to the signal. This is a significant draw back in sEMG. In a recent attempt to resolve this, (Spanias et al., 2015) proposed a classifier which is capable of identifying such channels and disregards the EMG data coming from that channel. This has significantly lowered prediction error compared to a standard Linear Discriminant Analysis (LDA) classifier in the presence of EMG disturbances.

In recent years use of sEMG arrays are popular in gesture recognition (Stoica et al., 2012), (Monica Rojas-Martinez and and Alons, 2012), (Tang et al., 2012). Having a high density electrode array that covers a larger surface area, provides a detailed map of the myoelectric signals. This eliminates the necessity of the careful placement of the
electrodes. With dry-electrodes, the author considers high density arrays are the most suitable approach in prosthesis applications.

Surface EMG is greatly susceptible to noise (Clancy et al., 2002) and electrically weak. Generally, sEMG signals suffer from signal drift, muscle fatigue, crosstalk (Merlo and Campanini, 2010) (Luca et al., 2011), cable motion artefacts (Clancy et al., 2002), motion artefacts (Merlo and Campanini, 2010), electrode impedance fluctuations due to sweat formation and positioning. However, in present day, commercially available robotic prostheses, rehabilitation robots and exoskeletons are primarily relying on myoelectric signals. Capturing and processing of these signals is a well-explored context. For better results, it is required to capture myoelectric signals from both anterior and posterior compartments of the forearm. In such cases, crosstalk of deeper and superficial muscles is inevitable.

In the context of myoelectric prosthesis control, the focus is on facilitating an externally powered prosthesis for an amputee. Interestingly vast amount of sEMG related work has been based on the data gathered from able subjects. Able subjects can perform both isometric and isotonic gestures at different resistive forces (Torque) by means of a dynomometer etc. However, with trans-radial amputees this approach impractical, although they can fully contract the residual muscles. With sEMG, predominately there are two notable problems;

- Problem 1: Isotonic tissue movement with respect to skin
- Problem 2: Having to attain the isometric contraction region/tetanic region to produce detectable and usable sEMG signal amplitude

This could be the reason behind the slow evolution of sEMG technology in practical dexterous prostheses control, although there are numerous current researches in the context. As previously mentioned, most of the data used for those researches were captured from healthy subjects. The lack of understanding of physiology of forearm amputees can also be a contributing factor.

Surface EMG technology has stagnated in terms of detection methods or hardware. Numerous current researches are primarily restricted to investigations on novel classification, recognition methods and improvements. This inevitably reduces the contributions and the novelties can be less-significant for the prosthesis control. None of the methods have satisfactorily demonstrated proportional control, which is highly affected by fatigue, noise and motion artefacts. It is also surprising to learn that the amount of work put in to obtain minor improvements in EMG by numerous researchers, rather than exploring new methods with a fresh prospects to extract data from skeletal muscles.
2.3.5 Near-Infrared Spectroscopy (NIRS)

Near-infrared (NIR) lies closest to the red colour in the infra-red band of electromagnetic spectrum with 0.75 - 1.4 um wavelength. A unique property of NIR is it absorbed by oxygenated and de-oxygenated haemoglobin in blood (Bozkurt et al., 2005). This property is widely been used in Pulse Oximetry, a non-invasive method to estimate person’s oxygen saturation in blood. In some studies, ability to detect brain activities also investigated (Yanagisawa et al., 2010). Interestingly, several studies have been done with NIR to investigate the feasibility to control prostheses. During the initial phases of the research, the author repeated the experiment conducted by (Herrmann and Buchenrieder, 2010) to investigate the possibility to use the technique to detect complex gestures from the forearm muscles. Figure 2.6 shows the preliminary results obtained by the author.

For the experiment, the NIR sensor using the same materials and similar physical dimensions was constructed as detailed in the paper. Surface EMG sensor was omitted. Sensors were placed on dorsal and ventral sides of an intact forearm and simple finger flexion/extension gestures were executed. Conflicting results were observed. Herrmans
have fixed the sensor over the flexor digitorum muscle. Our test did not show significant NIR variation at the same site. However, placing the sensor towards the tendon joints, significant NIR variation was observed. The reason for this phenomenon could be explained as the high density tendons reflected more incident NIR compared to soft tissues. Muscle tissues tend to absorb a large amount of NIR. Secondly, due to the longer distance between transmitter and the receiver, a negligible signal intensity was observed. Based on the results, we can conclude that the NIR may not be effective or reliable source to determine muscle activities, but placing the sensor over the tendons could improve the measurements significantly. Due to this weakness, application on trans-radial amputees is limited as most of the amputees lack usable amount of tendons.

(Kimoto and Y., 2012) presented a muscular activity sensing scheme with three sensors integrated into one. The sensor consisted of sEMG, MMG and NIR detection facilities. The experiment was merely designed to evaluate $\Delta$Hb and $\Delta$HbO$_2$ levels at an occlusion of the forearm with a cuff arrangement. Although there is a clear correlation between sEMG, MMG and the change in relative Hb levels during work and rest, the measurement accuracy was insufficient. This is caused by instability of the circuit, change in contact between the skin and sensor and ambient light. According to their conclusion, NIR is not a stable and reliable measurement of muscle activities in the forearm.

Two optical and piezo-cable muscle activity sensors (MAS) were presented by (Han and Kim, 2009) targeting the upper arm elbow related muscles, biceps and triceps, instead of forearm. The optical sensor is based on reflected light intensity, in which the approach differs from the NIR study above. They state that the muscle volume dictates the reflected light intensity. They concluded that the optical MAS can detect individual muscle activities precisely, which is logically acceptable. However, the piezo-cable (pMAS) sensor can only provide cross-sectional changes of collection of muscles. The cross-sectional changes occur during finger flexions in the forearm can be very small. In another similar study by (Cen et al., 2011), a comparison between sEMG and oMAS has been done with different levels of loads on the forearm. The results suggest a linear relationship between load and sEMG, which is good enough to quantify the force application levels of the muscle. However, it is questionable whether the technique is sufficient to detect deeper muscles in the forearm.

In a recent study by (Yao et al., 2014), a wearable, portable and wireless multi-channel NIR spectroscopy was presented to monitor blood oxygenation and hemodynamics. The system is proved to be accurate and stable although only two gestures indicated prominent light intensity and oxygen level variations. To validate the system, they have performed isometric voluntary forearm muscle contractions and obtained the Hb and
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H\textsubscript{2}O\textsubscript{2} levels. The results revealed a near-linear relationship. A researcher linked to the same group above (Guo et al., 2014) and (Guo, 2014) has taken the study further to pave the direction towards prosthesis control using the same hardware mentioned above (Yao et al., 2014). In both studies they have combined sEMG and NIRS to improve recognition rates of 13 hand motion classes. In the first study, combined EMG and NIRS outperforms other similar capturing devices. A time domain auto-regression model (TDAR) employed in the second study outperformed other feature sets. Best performance yielded from integration of time-frequency domain information from sEMG data and time domain information of NIRS. This resulted the most stable and highest classification accuracy of 98%.

2.4 Force Sensing

Measuring the force generated by the muscles is another feasible parameter to quantify the actions made by amputees or able subjects. FSR (Force Sensing Resistors) is a resistor that changes its resistance with applied force on it. In a study conducted by (Castellini and Ravindra, 2014) used 10 FSRs wrapped around proximal part of the forearm to deduce forearm surface muscle deformation. Since the FSRs are highly non-linear for higher forces, they have used only the linear region. Analysis revealed Ridge Regression (RR) performed worse in recognising the force whereas SVM and Random Fourier Features (RFF) showed similar results with nRMSE ranging from 5% to 14%. Although this method is suitable to recognize superficial muscle force or activities, it cannot reveal the deeper muscle activities. In an unique study by (Bu et al., 2009) Aluminium Nitric (AlN) piezoelectric thin film sensor was used to measure the muscle activities and establish the relationship between muscle cross-sectional changes (obtained by US images). Data was recorded during both isokinetic and isometric contraction of biceps brachii muscle. AlN sensor produced proportional voltage due to force exerted on it from muscle activities, similar to Castellini’s study mentioned above. However the results revealed that there is no clear correlation between muscle thickness change and the voltage output.

2.4.1 Physiological Changes

Within this category, several topics can be investigated. This is by measuring the physiological and electrical nature of the targeted area;

- Inductance sensing
Circumference change (Strain sensors)

Force

Fabric integrated strain and FSR sensors mounted on the forearm were used to interpret hand gestures (Amft et al., 2006). In this study, four everyday gestures such as, upward movement of lower arm, outward bending of hand, opening/closing hand and lifting a heavy object were investigated. Fabric stretch (strain) sensor exhibited high hysteresis. Strain sensor data deviated with the circumference of the forearm. FSR data suggested a strong correlation between muscle activity and the signal deviation. Inductance sensor (Karlsson, 2010) is another feasible application that will provide similar results as strain sensors. In this technique, a braided wire is woven into an elastic fabric, that forms a part of an oscillator. The wire acts as the inductor where its natural frequency varies due to stretching. The change in frequency can be linear in this occasion, however the principle is similar to the strain sensor.

2.5 Other Methods Used in Prosthesis Control

2.5.1 Speech/Voice Control

Apart from myoelectric or bio-signal detection methods, one of the most straightforward methods is speech commands. Speech recognition need no introduction as it used in many everyday applications. (House et al., 2009) demonstrated a practical application of the technology in prosthesis control based on Vocal Joystick inference engine. The method used non-verbal voice as control input. Although not categorized under scientific research, creditable effort has made by amateur designers (Patrick, 2015) to demonstrate the effectiveness of voice controlled prosthesis. Although this technology is comparatively simple and straightforward it has failed to get the required attention. Voice control can be a very efficient way of controlling the prosthesis without complex bio-signal acquisition and processing. The reliability and repeatability can be high. The user can program the hand with numerous commands to perform complex gestures. The voice control of prosthesis is a simple yet powerful method that requires further attention.

2.5.2 Brain-Machine Interface (BMI)

Paralysed patients due to stroke, spinal cord or brain injuries are not capable of activating the muscles. Therefore myoelectric or ultrasonographic approaches are not applicable. In such situations, brain-machine interfaces can provide a solution to overcome
the problem. It works on the basis of subject’s intention to act. It detects the electrical activities, Electroencephalography (EEG)) in the brain at the scalp by means of array of electrodes (Schwartz et al., 2006) (Li, 2014). However this method may require lengthy training sessions for individuals and intense mental exercises. In real-world situations, rapid control and response cannot be reliably achieved by this method.

2.6 Summary

To date, dexterous prosthesis controllers utilize only the myoelectric approach to recognize muscle activities. So far it has been highly regarded as reliable method to control prosthesis hands like ”i-Limb”. Although the potential of SMG is pointed out by a few researchers and it has not matured to the point where its practical usability. This mainly due to the lack of wearable and practical hardware including low-profile transducers. In terms of hardware concepts, EMG has not evolved over the last few decades. The concept is well understood and explored. The only considerable developments in sEMG took place in two directions. Modern semiconductor technology resulted more robust and efficient myoelectric detectors compared to transistor and OPAMP (operational amplifiers) based historical circuits. New instrumentation amplifiers provide high again but low noise sEMG detection schemes. The second notable improvement is the high-density EMG, in which a large number of equally spaced electrodes are used to acquire a signal map over the area of interest (AOI). This approach eliminates the requirement to carefully place the electrodes over the target muscles by specialists or trained individuals. Instead, one can wear the array as they wish and train the classifier to identify required gestures.

NIR is proved to be effective in certain conditions, if high density tissues, such as tendons and bones, present under the emitters and the receivers. This has been observed by the author. However its ability to detect deeper muscle activities still remains questionable and require further analysis. Mechanomyography (MMG) on the other hand provide more information than NIR. In addition to the amplitude of the vibrations and acoustics, frequency of the vibrations could provide further information. MMG requires proper contact with the skin similar to EMG/SMG to transfer vibratory and acoustic energies. However, one of the advantage of MMG is its ability to operate in moisture laden and underwater conditions as it is not measuring any electrical quantities. More studied are needed to improve the method further.

With regards to US capturing devices, it is evident that there have been no interests by the researchers to design wearable US hardware and transducer arrays to control prosthesis with SMG. All the existing major studies (mainly done by Zheng and his group
and Castellini) use standard US imaging systems. However there are some researchers who have developed low cost US hardware in order to improve US imaging qualities rather than to facilitate prosthesis control. The previous studies on SMG provide encouraging results with image based processing and recognition algorithms (Table 2.1 on page 39).
<table>
<thead>
<tr>
<th>Author</th>
<th>Hardware Type</th>
<th>Wearability</th>
<th>Portability</th>
<th>Configurability</th>
<th>Probe Type</th>
<th>Frequency</th>
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Chapter 3

Quasi-Radial Hardware

3.1 Introduction

This chapter details the construction, design, techniques and features of WURMADS (Wearable Ultrasound Radial Muscle Activity Detection System) hardware. WURMADS is the purpose-built hardware for this research. According to the available literature, WURMADS hardware is the only practical approach to address the portability and wearability aspects of Sonomyography (SMG) in the dexterous prosthesis control.

The hardware is primarily comprised of two sections.

- Wearable transducer ring assembly
- Base station with control electronics

During the development phase of WURMADS, it went through several versions and improvements. US hardware development in medical context requires a high quality electronic circuit design and components. This is one of the reasons that majority of the researches in US muscle activity detection are preferred to use standard commercially available US imaging systems. That is only for the experiments without investing time on new hardware solutions. During the development phase of WURMADS, the author spent considerable time on experiments to test numerous methods in order to fulfil the fundamental requirements to meet the research objectives. The preliminary requirement specification for the hardware are as follows.

- Portability
- Wearability
Chapter 3. Quasi-Radial Hardware

- Compact and lightweight construction to integrate inside prosthesis sockets
- On-board processing capability
- Electronic architecture that comply with safety regulations for ultrasound
- Rechargeable battery operation and efficient power management system for lengthy operation

The wearable US ring construction is equivalent to a standard medical US probe, with lower resolution. However, in WURMADS, this construction must satisfy the following requirements.

- Easy wearability
- Adjustability
- Low profile design that could potentially integrated into a prosthesis hand assembly
- Waterproof construction to withstand sweat, humidity and high temperatures.
- Immunity to electrical noises that may be picked up by the wiring looms
- Rigidity to prevent transducer slippage and undesired movements

WURMADS has two US transducer assemblies with 5 and 3 elements attached. In standard medical US systems, this is equivalent to the probe, although ours is low resolution. US transducers are considered as one of the most expensive parts of the system. In medical domain, a standard probe may costs above £1000 in most instances. The physical structure can also be varied depending on the application. For example, in Doppler mode where it measures the speed of blood flow in blood vessels, requires a narrower or a single element probe. The base station is a collection of analog and digital electronic circuitries to transmit, receive and process acoustic signals. The systems found in medical context, circuits can be extremely complex and expensive. It should be noted that the application of WURMADS and professional medical US devices is contextually different. Medical US systems are designed to provide only a visual feedback; dimensional calculations (to acquire sizes of organs, muscles, etc) to satisfy clinical diagnostic requirements. Therefore, the user interface is constructed in such a way to provide highest possible spatial resolution and dynamic measuring features.

On the other hand, WURMADS has a unique construction with on-board processing facilities without a graphical user interface. The resolution is also inferior to professional systems as there are smaller number of US channels. However, the objective of
the WAURMADS hardware is to detect morphological changes in the forearm without providing high-resolution visualization. Although this is technically possible with the current hardware set-up, dexterous prosthesis control and gesture identification are the fundamental functional requirements. Conventional US systems generally lack the aspects of portability and wearability. Almost every commercially available systems are bulky, requires the mains power and impractical to wear on a forearm without specially adapted apparatus or cradle. During the design phases of WURMADS, the author took necessary steps to integrate the above requirements which are unavailable in neither commercially nor research level US muscle activity detection systems. The physical assembly of transducers is depicted in Figure. 3.1.

3.2 Quasi-Radial US Ring Construction

The term Quasi-radial is first suggested by the author. The application lies within the context of Sonomyography. According to the available literature to date, there are no similar studies on utilizing ultrasound (or SMG) with multiple transducers in a radial construction. The only exception is the studies done by Guo with standalone single element transducer (Guo et al., 2008a,b, 2009a). Specifically, the author would like to stress that the researches in the similar context always utilized standard US probes to demonstrate the methods. WURMADS uses two radial wearable rings with eight integrated 5MHz transducers. The holder in which the transducers are fixed is made out of ABS (Acrylonitrile Butadiene Styrene) plastic for rigidity. The larger and smaller rings consist of five and three transducers respectively.

In the context, widely discussed methods is in-air gesture recognition. This is a recently emerged field that uses low cost, low frequency transducers to recognize gestures for human-machine interactions, especially for mobile devices. US has been using in recent years for heptics or kinaesthetic feedback. A research by Tom Carter of Bristol University UK, presented "UltraHeptics" to provide multipoint heptic feedback using low frequency US waves. However, this method cannot be adopted in amputees or to control dexterous prosthesis due to limitations. Apart from heptic feedback and mid-air gesture recognition, an interesting study by Adiyan Mujibiya of Tokyo University (Mujibiya et al., 2013), presented a method for on-body touch and gesture recognition based on transdermal US propagation. The concept uses low frequency US transducers assembled in rings.
3.2.1 Geometry of the Ring

Two rings associated with WURMADS can be worn in different ways to suit the amputees preference and level of comfort. However, the rings must focus on one or more muscles in order to capture morphological changes as required by SMG. If more channels are used, more gestures can be potentially recognized.

Ideally, 5 transducer (r1) ring is fitted on the ventral side of the forearm (Figure. 3.2) where the majority of the muscles are easily be accessed. Three transducer ring can ideally be fixed on the dorsal side since ulna and radium bones shadow a considerable portion of 5 transducer ring’s energy. It helps to acquire extensor muscle activities. Average forearm circumference of an adult is 10-12 inches. However, the radius of the curvature can differ due to the oval shape of an average forearm cross-section. Therefore the two rings with the same radius have two focal points, hence naming the geometry as quasi-radial. Note that the curvature radius of the rings are \( r_{\text{ring}} \leq r_{\text{ventral/dorsal}} \) surface. The rings can be fixed at different places along the forearm length.

Currently WURMADS only support 8 channels (Transducers) but it can be easily
doubled or tripled with hardware modifications. In addition to Quasi-Radial geometry it is also possible to arrange transducers in different formations on a 2D plane. There is no available literature suggesting a similar arrangement to the one we presented here. However in sEMG forearm gesture recognition context, a few studies have adopted wearable ring formation. The most attractive of all is the commercially available "Myo" armband which is a wearable wireless gesture control and motion control device (https://www.myo.com/).

Figure 3.4 on page 46 depicts the practical applications of the rings, photographed during the data collection sessions using the WURMADS hardware in 2014.

The rigidity of the ring is important in order to prevent motion related artefact. One of the advantage of low-resolution US is, slight movements cannot significantly make an impact on the output unlike in probe based high-resolution systems. Secondly, it requires comparatively simple hardware. However during pronation and supination, relative movements of skin and muscles greatly affects the echo profiles.

### 3.3 WURMADS Transducer Construction

The primary component of the wearable rings is the transducer element. In the context of ultrasound transducers, they can be divided into two main categories, air-coupled or liquid coupled. Construction wise air-coupled transducers are less intricate than the
Figure 3.3: Quasi-Radial Geometry on forearm. A - Ventral side. B - Dorsal side. C - Plane of section

liquid coupled. The most well known application of air-coupled US is the parking sonar of automobile, new motion capture methods (Sato et al., 2010), motion detection for automation and hand gesture recognition in air. Transducers used in such applications are commonly available and cost less.

Apart from medical applications, high frequency US is particularly used to interrogate composite materials for flaws, porosity, foreign materials and bonding joint failures. Air-coupled transducers are typically operated below 1MHz as the attenuation is high beyond this frequency range (Hedrick et al., 2005). The primary reasons behind inability use air-coupled US in medical application is the safety and high attenuation. The large differences in acoustic impedances between air and the skin demand very high incident energy to overcome the resistance. This can be hazardous and impractical in medical applications. Majority of air-coupled applications are single channel C-Mode (Constant depth) scan systems (Buckley, 2000). Studies that have been conducted on Non-Contact Ultrasound (NCA) by (Bhardwaj, 2001) (Clement et al., 2013) demonstrated the feasibility of using it on human tissues. However, there is more work is needed to be done on the techniques to use on human subjects to detect muscular activities in finer resolution. The penetration depth could also be limited. If the frequency used is lower, details of the acquired images could be limited. This method is used in some industries as it doesn’t
Figure 3.4: Levels of different trans-radial amputation of subjects that participated in data collection sessions in Sri Lanka
require the application of coupling medium (gel, oil, water, etc), so the tests could be quick and clean.

Liquid coupled transducers are widely used in various industries including NDT (Non-Destructive Testing). All available US probes used in medical fields are liquid coupled. Therefore, the author omitted further investigations on air-coupled US techniques as the challenges and problems superseded the possible benefits.

US transducer element is the most important part in any US system, whether medical or industrial. A piezoelectric crystal is the primary element in the transducer that produces the vibration. There are numerous applications of US transducers, spans from medical imaging, automation, cleaning, industrial NDT to personal beauty and therapeutic applications. However, the focus of the discussion is confined to the medical context. Medical US probes mainly come in linear, sector and curvilinear construction, which is governed by the shape of the transducer element array. Contrary to linear and sector, in curvilinear/curved arrays, the ceramic elements are arranged along an arc where the radius is normally 25-100mm (Hedrick et al., 2005). Note that proposed quasi-radial construction of the transducer array in this study, also follows this principle, but in a larger physical scale with low lateral resolution. The literature says that the curvilinear construction loses the lateral resolution (Hedrick et al., 2005) due to the decreased in line density.

For our application of this technology, axial resolution is the imperative feature. Apart from curvilinear construction, 360 degrees radial-array transducers (Zhou et al., 2014) provide panoramic visualization of internal organs and endoscopy. The difference of this method is it monitors outwards, whereas our solution monitors inwards. In sector scan probes, a single element transducer is used and a motorized mechanism sways the transducer element in an oil (or suitable coupling medium) filled compartment. To measure the instantaneous angle, a high resolution encoder is normally integrated into the motorised mechanism. Ideally mechanical sector scan approach is suitable for applications for prostheses control as it only contains a single transducer, resulting less intricate electronics. However, motor and mechanical assembly can take a considerable space making it cumbersome to wear or integrate into a dexterous prosthesis.

3.3.1 Materials

Transducer manufacturing process is complex. The techniques used and the exact material compounds are safely guarded as industry secret by medical range transducer manufacturers in the world. The construction of the medical frequency transducer relies on the phenomenon first observed by Pierre Curie in 1880 and is called piezoelectric effect
This effect is commonly found in crystalline materials that have dipoles on each molecule. The electric polarity change across the crystal, causes it to expand and contract. This produces a mechanical vibration. The thickness between the two sides governs the natural frequency of the crystal (3.2 on page 50). The piezoelectric material that we have used to construct the transducers is Lead Zirconate Titanate (PZT). There are several grades of this material and the one that we have used is PZT-5, which is widely used in medical transducers as it has the desirable properties. Such as high-electromechanical coupling coefficients, malleability and high dielectric constant. Apart from PZT, Barium Lead Titanate, Lithium Sulfate, Lead Metaniobate and Lead Zirconate are also used for the crystal.

WURMADS transducers are manufactured by Shenzhen Hurricane Tech.Co Ltd, China to mechanical and electrical specification defined by the author. They modified a muscle thickness measuring transducer that originally designed for a Japanese customer in Cattle industry to measure muscle thickness, to the given characteristics. In some instances dopant are added to meet certain electrical requirements such as to withstand large acoustic power and electrical impulses (voltage swing).

Ring-down (or resonance) is a serious problem in transducers. This occurs due to electrical ringing and vibration of the piezoelectric ceramic structure according to (Ana and O’Donnell, 2002). However in other literature (Hedrick et al., 2005), ring-down is referred as artefacts generated due to gas filled bubbles that resonate, creating a large artefacts within the near-field close to the surface of the transducer. Therefore the definition is slightly conflicting and questionable. However the first definition is more technically logical. Figure. 3.5 depicts the internal construction of the transducer element.

![Figure 3.5: WURMADS: Internal construction of the transducer](image)


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Table 3.1: Transducer specification: Electrical characteristics

3.3.2 Frequency Selection

The frequency selection is carried out following a several experiments. In these experiments optimum frequency for forearm muscle activity visualization was evaluated. Prior to this, we analysed a medical US system with different probes to visualize forearm morphological changes. However the exercise failed to provide better insight into the frequency and resolution. The transducer’s mechanical characteristics were fixed to the above dimensions (Figure. 3.5). We procured identical transducers with different frequencies from 1MHz - 10MHz for the experiment while maintaining the same physical size/shape. The experiment revealed that the higher frequency signals indeed attenuate to a greater extent than the lower counterpart due to scattering and absorption. Figure. 3.6 shows the screen captures obtained at 5MHz and 10MHz signals with identical test conditions and excitation pulse amplitude.

![Figure 3.6: Signal attenuation comparison under identical test conditions. A - 5MHz. B - 10MHz. Without Time Gain Compensation (TGC)](image)

The signal amplitudes at 10MHz clearly shows a high attenuation and inability to reveal finer details. At 1MHz, signals penetrate deeper, however due to the longer wavelength, it fails to record finer details or produce enough reflection from echogenic boundaries.
Higher the frequency, shorter the wavelength (3.1) and increases the spatial resolution. As a compromise between the resolution and penetration, we concluded that the best suited frequency for forearm applications is 5MHz. At 5MHz most finer details and movements were satisfactorily recorded and exhibited good penetration depth, whereas 10MHz had a very limited depth for the application.

WURMADS is only interested in axial resolution rather than lateral. Quasi-radial construction of the ring cannot be reliably used for visualize structures that lying side by side. However, it can achieve good axial resolution as presented in Chapter 4. If one wavelength is a good approximation of the smallest detectable object, with 5MHz pulse frequency, the resolution would be $c/5 \times 10^6$, where $c$ is the speed of sound in the medium. (Based in 5 pulse burst).

$$\lambda = \frac{c}{f} = \frac{1540}{5 \times 10^6} = 0.308 \text{mm}$$

(3.1)

where 1540m$^{-1}$ is the US velocity in soft-tissue and $f$ is the pulse frequency. In practice, at 5MHz, penetration depth of 20cm can be achieved with spatial resolution of 0.5-1.0mm. (Gibbs et al., 2009).

Thickness of the ceramic governs the fundamental frequency. This is also calculated by the equation 3.1, taking the speed of sound in PZT ceramic as 4350m$^{-1}$. The standard thickness is considered to be $\lambda/2$. Therefore the ceramic thickness is given by,

$$\lambda = \frac{c}{f} = \frac{4350}{5 \times 10^6} = 0.87 \text{mm}$$

(3.2)

$$t_{PZT} = 0.87/2 = 0.435 \text{mm}$$

3.3.3 Backing Material

For the liquid coupling transducers, ideally it is required to absorb all the energy that goes in the opposite direction and prevent ringing by damping the crystal. For this to occur, the acoustic impedances of the backing material must be identical to the piezoelectric ceramic or the crystal. The commonly used backing materials in diagnostic transducers are the epoxy resin and tungsten powder. In some cases pyrolytic, brass and carbon are also used (Brown, 2000). In our transducers, epoxy resin is used. As depicted in the Figure. 3.5 on page 48, rear surface of the backing material is slanted in order to prevent energy reflection back into the ceramic crystal. In some cases dynamic damping
is used in which the opposite phase voltage pulse is applied following the excitation pulse
to inhibit undesired ringing of the crystal. The timing must be precisely calculated.

3.3.4 Front Acoustic Matching Layer

Matching layer provides a smooth interface between the crystal element and the skin
to allow maximum energy transfer. Higher acoustic impedance causes a large amount
of energy to be reflected back to the transducer, hence diminishing the performances.
Theoretically, thickness of the matching layer is $\lambda/4$ of centre frequency. This allows
the waves that are reflected to be in-phase when they exit the layer. In advanced and
more expensive transducer arrays, multiple or tapered matching layers are utilized to
allow broader bandwidth. The transducers we have used consist of a single matching
layer. The acoustic impedance of this material is derived by taking the geometric mean
of the crystal and the tissue (3.3, where $Z_c$ and $Z_t$ are the acoustic impedances of crystal
and tissue respectively). The crystal’s acoustic impedance is said to be 30Mrayls and
1.6Mrayls for the skin (tissue) interface. Without a matching layer, the amount of energy
reflected back at the interface is 81%.

$$Z_{ml} = \sqrt{Z_c Z_t}$$ (3.3)

The geometric mean equation gives the required acoustic matching layer value as 6.9Mrayls.
A material of this acoustic impedance will produce an efficient interface while transmitting 61% of the energy into the tissue. According to the current technologies, there is no technique to transfer all the energy into the tissues without losses.

The acoustic matching plays a significant role in applications to control prosthetic limbs.
Longer wearing period tends to dry out coupling mediums such as US gel, and increases
the acoustic impedance between skin and the transducer. If the matching layer is tapered
and close to the skin’s, reduced impedance will result better transfer of acoustic energy.
However more research is required on special materials to fulfil this requirements. A
practical solution for the drying out of coupling medium is presented in Chapter 7.

Acoustic impedance ($Z$) is a property of a substance (Human soft tissues in this case)
described as how the particles of that substance behave when subjected to an acoustic
pressure wave. If the substance has densely packed particles (high density) such as bone,
then it will take higher pressure for them to move at a given velocity (Gibbs et al., 2009).
Such substances will have higher acoustic impedance.

$$Z = \rho c$$ (3.4)
3.3.5 Electrodes and Casing

The electrical connection to the piezoelectric ceramic has two silver pads with wires soldered. In compact arrays gold connecting pads are used to provide better conductivity. The outer casing that contain backing material, crystal and the matching layer is made of copper for rigidity without any electrical connections for safety considerations. In some designs the casing is grounded. However, a proper electrical isolation is recommended.

3.4 WURMADS Electronic Architecture

In this section a detailed description of the electronics architecture is provided. The control strategy of WURMADS is hierarchical. The DSP acts as the high-level supervisory controller that oversees the other sub-systems. Design, construction and assemblies of WURMADS circuitries were carried out in order to comply with EMC/EMI and smaller footprint. A three-stage wire-free plug-in type construction was introduced to impose rigidity. With the use of Surface Mount Devices (SMD) it is feasible to construct low-profile Printed Circuit Boards (PCB) which allows stackable expansion while keeping the same footprint or the form-factor. A recent similar construction method can be seen on Raspberry-Pi development kit. Its expansion boards only use header connectors instead of wired. These header connectors provide extra rigidity to the construction preventing undesired bending and twisting.

The front-end electrical architecture is similar to common US systems (Brunner, 2002). The transmitter mode of WURMADS is fixed to "Pulse", although it is possible to change to CW/PW Doppler modes with software upgrades. But that lies out of the scope of this thesis.

3.5 Hardware/Software Methods and Justification

This section details the signal processing aspects (Quistgaard, 1997) of the WURMADS electronics architecture. The professional circuit design tools and simulations were deployed during the design stages of WURMADS. It has many levels of operations, which are discussed in detail in this section. In addition, justification for the construction process and methods are also discussed.
3.5.1 On-board Processor Selection

Majority of the researches on medical US hardware development utilize FPGA (Field Programmable Gate Array) approach to handle crucial tasks within the system. At a glance, it is evident that the preferred processing methodology used in medical US systems is FPGA (Hassan, 2014) (Hassan and Y.M., 2011).

In a nutshell, FPGAs are primarily suited for applications with parallel processing/multithreading where higher data bandwidths are required. Particularly in US applications, demand for high-speed I/O (input/Output) attracts FPGA solutions. This is mainly due to the ability of generating dedicated processes independent of the functions within a FPGA environment (such as interrupts). The functional execution and coding of DSP and FPGA are completely different. DSP software is based on sequential execution of instructions, but FPGA is mainly following parallel execution. In another words, FPGA will take a single clock cycle to execute a function, whereas a DSP may take 1000s of clock pulses to do the same, which is an attractive feature as far as latencies are concerned. A FPGA is a sea of gates that can be programmed to create a circuitry to serve
the requirements in independent blocks. The processors can run in parallel without interrupting or affecting the other functional blocks. Where high-density US transducer arrays are used, beam-forming requires a critically timed pulses to be generated and processed. This can only be satisfied by allocating independent modules created in a FPGA. Dedicated silicon segments or gates within a FPGA can outperform DSP I/O handling by many folds in terms of speed and response time. This is the fundamental reason behind the usage of FPGA in medical US systems, as most of it supposed to operate above 3MHz.

However, one of the notable weaknesses of FPGA is its inability to share algorithmic processes like FFT, complex interrelations and data manipulation. If the requirements are complex, FPGA demands logical blocks for each and every process making the entire architecture overly intricate and may cause metastability issues (when data is shared between modules asynchronously). In order to run complex software with a large amount of mathematical functions, top of the range, high-energy consuming (due to large number of gates), expensive FPGAs are required. However the abilities of modern DSPs cannot be undermined. (Li and D.C., 2009) proposed a system which has the capability to process ultrasound signals of B mode, color flow and spectrum Doppler in real-time. The system used four high performance DSPs (TMS320VC6416) with on-board memory chips to act as the programmable back-end. Generally US systems can be built around FPGAs only if there are no complex algorithms to be executed. For example (Dusa et al., 2014) (duck Kim et al., 2012) proposed single FPGA systems for both front-end and back-end processes.

One of the goals of the research is to produce the hardware within a shorter span of time, efficiently and reliably. It also required to fulfil the initial hypothesis made to construct a wearable system to control dexterous prostheses. The previous experiences the author brought into the research, it is understood that the FPGA path may take longer to develop, customize and troubleshoot in certain conditions which may jeopardize the time-scale of the research. Apart from workload involved with FPGA, another reason behind the decision to take DSP path is the difficulty of implementing algorithmic processors involved in gesture recognition. Also this must be executed on-board in real-time. If FPGA is used, this will extensively require time and effort to meet the requirements and logic block design. For example, Hilbert transform code requires a several blocks of functions that can easily implement in a DSP environment, whereas in a FPGA the same code design may take days in Hardware Description Language (HDL). This could have negatively impacted the time-scale. The second important factor was
the PCB design complexity and cost. Most FPGA chips in the market require a multi-
layer Printed Circuit Board (PCB with more than 2 layers).

The current WURMADS circuits are based on cheaper 2-layer PCBs. A 4 layer PCB
will cost nearly 3 times the price of 2 layer, raising the prototyping costs enormously.
Also FPGA chips commonly come in BGA packages which are difficult to assemble by
hand. Generally, FPGA designs consume more power than DSP equivalent. This is
particularly unattractive in portable systems considering the WURMADS is designed
as a portable standalone system. In future designs, electronics will be fully integrated in
the garments or in the prosthetic hand itself. With a design based on a multilayer PCB,
this task will be extremely difficult. To support such flexibility, the electronics must be
assembled on a flexible PCB (Flex PCB). Generally multi-layer flex PCB fabrication is
extremely costly and unattractive option for the research.

DSP programming is based on C/C++ language and it is highly standardized in the
field. There are numerous support and free libraries, which are beneficial in reducing the
development time. New advancements like 3D/4D US imaging demands dedicated signal
processing schemes with more mathematical operation with image processing (Ali et al.,
2008). Although advanced 3D/4D image processing not implemented in WURMADS,
DSP processors are proven to be efficient in mathematical operations with reduced costs
(Li and D.C., 2009).

Finally, the DSP route was favoured over FPGA after weighing the advantages and
disadvantages carefully. The selected DSP was dsPIC33EP512MU814 16-bit processor
by Microchip Inc, Arizona, USA (Appendix B.2), which is a technically capable processor
for our application. However, it was an unknown territory to design a medical range US
hardware based on a single DSP. This is due to the lack of literature and similar research
context to justify the DSP benefits in front-end of medical range US applications. In
modern high end US systems, processing is shared among DSP and a FPGA. FPGA
mainly handles beam-forming and receiving and the DSP mostly handles the signal
processing and graphical user interfaces (GUI). Techniques like apodization (Hassan
and Kadah, 2013) isn’t used as the image construction approach of ours is contextually
difference.

3.6 Modular Construction

This section details the modular structure in WURMADS that designed to satisfy the
transmit/receive requirements.
Transmit Beam-former electronics

- Logics and channel routing
- Amplifier and Tx/Tx switches
- VGA and filtering
- ADC and FIFO buffering
- On-board or external processing and communications

Items in blue and red font denote the front-end and back-end sections.

Figure 3.8 describes the modular low-level functional block diagram of WURMADS. In the following sections, unique design methods and functionalities of each modules will be discussed.

![Diagram of WURMADS hardware construction]

Figure 3.8: Three layers of WURMADS hardware construction

3.6.1 Transmit Beam-Former Electronics and importance

Beam-forming is an important topic in medical US imaging, however it is trivial for WURMADS hardware. Beam-forming by utilizing delay-lines is not implemented in WURMADS due to the naturally focussed transducer assembly (Quasi-Radial). Although the system is capable of adding delays to each channel, it was not required to obtain A-mode signals to investigate morphological changes. In standard medical US
systems beam-forming is mainly handled by the FPGA. In WURMADS, a dedicated standalone transmit beam-former is utilized to distribute the workload from the DSP.

### 3.6.2 Power Management

Power supply circuits of WURMADS must be efficient and ripple free in order to reduce possible switching noises that may negatively impact the small signal amplifiers. The circuit schematics for this section can be found in Appendices B.3,B.4. New prototype versions of WURMADS were based on Point of Load (POL) power supply strategy (Brown, 2011). However the previous designs based on distributed power bus topology, demonstrated poor noise performance and Signal to noise ratio (SNR) at VGAs. To fulfill the portability requirement, the system is powered by a 12V Lead-acid rechargeable battery which is housed in the wearable enclosure. The battery is sealed and has the capacity of 2 Ampere Hours (Ah). The low profile battery can be easily housed in the prosthesis socket and weight around 0.5kg. Alternatively, it can also be placed inside a wearable pouch. The lead acid batteries are generally safer than the Lithium Ion /Polymer technology for body worn applications. WURMADS does not demand high inrush currents but continuous and steady. When the prototypes were tested without sleep modes enabled in the processors, the system drew approximately 150mA. For portable systems this is considered high but with the addition of sleep modes this can be lowered down by 70%. With the current power consumption rate the system is operable for 13.3 hours and potentially be increased to 22.6 hours, which is close to a day. However more power may be required to drive motors and actuators in the prosthesis hand in addition to the electronics in WURMADS.

To improve the efficiency in power regulation, the author designed the high-drop voltage regulations using DC-DC converters (Acopian) which are 70-85% efficient than low-dropout (LDO) linear regulators. In addition, the attractive feature of DC-DC converters is the ability boost voltage in cases where $V_{\text{in}} < V_{\text{out}}$. Greater losses occur during linear regulation, for example, when reducing voltage from 12V to 5V. Difference of 7V will dissipate as heat depending on the internal resistance and load current. In DC-DC converters, current is regulated by monitoring the load while maintaining the required voltage level using an inductor/capacitor arrangement.

As depicted in Figure 3.9, battery voltage (12V) is dropped to a lower voltage ranges by two DC-DC converters. 5.5V DC supply is based on LMZ22008 (Texas Instruments, Dallas, Texas) that feeds four LDO linear regulators. This voltage reduction helps to dissipate less power at the linear regulators and assisting the battery to last longer. The
second DC-DC is a negative voltage generator for VGA (Variable Gain Amplifier) and beam-former electronics, that based on PTN78000A (Texas Instruments, Dallas, Texas).

Power supply for the US related electronics must be properly regulated to meet certain safety aspects. High Voltage (HV) pulser can withstand voltages up to ±90V, which is acceptable in medical imaging. To satisfy the above criterion, two standard HV DC-DC ICs (HV9110NG, Supertex inc., 1235 Bordeaux Drive, Sunnyvale, CA) were used to generate higher voltages with required current levels.

Testing with prototypes revealed that the HV pulses to the transducers produce excessive amount of high frequency (HF) noise during positive and negative going transients (also known as transient noise). This is a common phenomenon in digital circuits, however this notably prevalent in US systems as pk-pk voltages of pulses can be as high as 180V. These HF noise spikes can adversely affect the performances of small signal amplifiers and other sensitive analog electronics. Regardless of careful board design and track layout with ideal ground loops, HV pulse noise spikes are extremely hard to get rid of due to its high-frequency component. This noise is affecting directly and indirectly. In the direct influence, the spikes are readily adding to the DC buses that carry power to various sections in the system. Indirect interference occur due to the emission of a short electromagnetic (RF) bursts. These short RF bursts can induce noise on high impedance PCB traces. If the trace is carrying a low voltage analog signal to the amplifier, it can be severely affected. Although it is difficult to eliminate both types of noises completely but shielding and low pass filtering can effectively decrease the noise. Second-order passive
LC low pass filtering scheme on power buses is implemented in order to minimize the adverse effects.

Figure 3.10 depicts the noise induced on low voltage rails when a burst of pulses being transmitted to a transducer. Top graph is taken at a point near the power entry point to the VGA circuit. The second graph depicts the LC filtered waveform at the VGA in which the noise is reduced by nearly 60%.

3.6.3 Variable Gain Amplifier (VGA)

VGA stage of WURMADS is based on a well established amplifier chip AD604 (Analog Devices, Norwood, MA 02062-9106, U.S.A) which is widely used in medical ultrasound systems. This amplifier has been first introduced by (Brunner, 1995) for its ultra-low noise VGA block which is ideal for the operation in the compact WURMADS electronic environment. The linear-in-dB gain response is given by the equation

\[ G \text{ (dB)} = (\text{Gain Scaling (dB/V)} \cdot \text{VGN (V)}) + (\text{Preamp Gain (dB)} \cdot 19 \text{ dB}) \]

The gain scales linearly in decibel with control voltages (from DSP) of 0.4 - 2.4V with the 20dB/V scale. The pre-amplifier gain of AD604 can be programmed to either 14dB or 20dB with the help of internal resistor array.
Chapter 3. Quasi-Radial Hardware

Figure 3.11: Gain curves vs gain control voltage

\[ \text{G (20 dB/V)} = 20 \quad \text{VGN 5, VREF = 2.500 V} \implies C \]
\[ \text{G (20 dB/V)} = 30 \quad \text{VGN 5, VREF = 1.666 V} \implies B \]
\[ \text{G (20 dB/V)} = 40 \quad \text{VGN 5, VREF = 1.250 V} \implies A \]

Electronics schematics are given in Appendix B.5.

3.6.4 Time Gain Compensation (TGC)

US signal attenuation in tissues is compensated by TGC technique (Jiajian, 2010). The signal attenuation and its impact is discussed in a latter section. In WURMADS hardware, TGC is controlled by the DSP through a Digital to Analog Converter (DAC). The voltage ramp increases the amplification gain linearly. The gradient is a function of depth. This also helps to maintain the image uniformity, specially in A-Mode. Figure 3.12 shows the linear map coded in the DSP’s firmware that sets the VGA’s (AD604) gain with respect to time. The increment is linear upto 48dB of maximum amplification, although the attenuation can be non-linear.

Figure 3.13 on page 61 depicts the practical application of TGC to overcome the attenuation as the signals penetrate deeper into the tissues. (A) - denotes the muscle boundaries. As the depth increases, the amount of energy being reflected is lower. This causes the amplitude of the reflected echoes to diminish (B). Proportional increment of the VGA gain (C) by the DSP with respect to depth, will maintain a constant amplitude...
Figure 3.12: Time gain curve for WURMADS. The slope is adjustable by the DSP. The maximum achievable amplification is 48dB.

(D). In B-Mode US, this is important to keep the echogenic boundaries brighter as the depth increases.

Figure 3.13: Time gain compensation: Practical consideration
Appendix B.5 details the electronic schematics for the above section.

3.6.5 ADC and FIFO Buffering

In most embedded electronic systems, ADC modules are normally integrated in the Microcontroller units (MCU). ADC modules are normally classified according to its sampling speed (Samples per Seconds or SPS) and resolution (Bits). In high-end MCU or DSP units, ADC sampling speed lies below 1MSPS. For example, high-end DSP unit used in WURMADS (dsPIC33EP512MU814) has 1.1MSPS ADC module. In medical imaging US systems, sampling speed requirement is above 20MSPS for acceptable performances.

LVDS - Low Voltage Differential Signal;

The output of the VGA is single-ended. At higher frequencies this is undesirable and prone to noise distortions. Therefore, VGA single-ended output is converted to LVDS before it being fed into the Analog to Digital Converter (ADC). Converting to differential signals have several advantages,(Brooks, 2001).

- Effective isolation from the power circuit and independent of ground.
- Noise immunity
- Improved signal to noise ratio

It is also required to have the PCB copper traces to be of same size and run as close as possible to each other. This is a common practice in US circuits to carry high frequency signals as differential signals. Differential driver chips must be used to convert single ended signal to industry standard LVDS levels.
WURMADS ADC is based on AD9203 (Analog Devices, Inc. Norwood, MA, USA), which is a 10-bit, 40MSPS converter designed for medical US applications. Its input voltage range is adjustable between 1 or 2V peak to peak. For faster processing, resolution is set to 8 bits (3.5) which is still sufficient to ensure good performance in the application. WURMADS ADC sample speed is set to 20MSPS and single channel design reduces the circuit complexity. This is however adjustable by the DSP. The clock is supplied by a serial port (SPI - Serial Peripheral Interface) programmable oscillator, LTC6903 (Linear Technology Corporation, Milpitas, CA, USA). The oscillator is programmable up to 68MHz with 0.1% maximum error. Serial Peripheral Interface (SPI) is used by the DSP to configure the oscillator at the system boot-up. However the output of the oscillator is logical NAND gated to provide added controllability to the DSP (Figure. 3.15). In high-end US imaging applications, each channel has its own ADC. With 2V pk-pk input voltage, the system resolution can be calculated as follows.

$$Resolution(R) = \frac{V_{p-p}}{2^n} = \frac{2}{2^8} = 7.8mV.$$ (3.5)

where $R$ is the voltage presented by LSB, $V_{p-p}$ is the voltage range and $n$ is the digital bit resolution. Figure. 3.15 shows the interface between VGA, ADC and NAND logic.
control.

\textbf{Figure 3.15:} VGA and ADC interface. Single-ended VGA output is converted to LVDS before the ADC stage.

Appendix B.5 details the electronic schematics for the above section.

3.6.6 Buffering

WURMADS has a unique buffering scheme to address the data bottlenecking issue that takes place when data is accessed by two asynchronous processors. The basic flow diagram is given in Figure 3.16. The system is build around AL422B (Averlogic Technologies, Inc, San Jose, CA, USA) 3M Bits FIFO DRAM. Independent read/write operation allows the DSP to read registers continually without affecting the ADC sampling speed. This technique effectively contributed to eliminate the FPGA approach for the WURMADS, although DSP input handling speed is inferior to FPGAs. Since the amount of handled data is much smaller than a conventional US system, it was well within the capability to use a FIFO approach to address the asynchronous problem that prevails without a FPGA.
To comply with clock synchronization and ADC parallel data load requirements, original ADC clock is phase shifted by $180^\circ$ using a precisely tuned capacitor-resistor arrangement on the clock distribution line.

### 3.6.7 Logics and Channel Routing

US pulse output from the transmit beam-former is complementary. In low cost portable US system, there is nothing between the beam-former and the transmit pulser, (Brunner, 1995) and (duck Kim et al., 2012). WURMADS hardware, however has an additional layer in between the HV pulsar and the beam-former to select channels individually. This layer serves as a simple, quick and efficient solution to select the required channels to be pulsed, instead of configuring the beam-former each time. The Microcontroller enables
the individual channel by enabling logical OR gates (SN74LVC1G32, Texas Instruments, Dallas, Texas). The block diagram is shown in Figure. 3.17.

![Block Diagram](image)

**Figure 3.17:** Additional layer to facilitate independent transmit channel selection

Electronic schematics for the channel routing section can be found in Appendix B.7.

### 3.6.8 HV Pulser and TX/RX Switches

Ultrasound pulser is a transmitter that amplifies the input beam-formed pulses. Small logic level signals in the order of 3-3.3V is amplified to swing between the pulser’s positive and negative HV voltages. The output of the pulser is connected to a transducer. In some cases voltage swing can be as large as \( \pm 180V \). In the literature several researchers have developed methods to integrate HV pulsers into CMUT(Capacitive Micro-machined Ultrasound Transducers) with advanced semiconductor technologies, (Savoia et al., 2014),(Zhao et al., 2011). In these researches a common denominator is the new silicon die construction to a smaller and power efficient configuration. (Banuaji and Cha, 2014) presented a HV analog front-end (AFE) integrated circuit with 15V pk-pk voltage swing, 0.15mm\(^2\) small footprint in the silicon die, which is ideal for large CMUT arrays as the size of the IC can be smaller. Electronically, theory behind the HV pulser circuits are well-understood. Per channel, the main components are the two MOSFETS (Metal Oxide Silicon Field Effect Transistor) that are arranged in such a way to form a half-bridge to drive the transducer. Novelties are lie upon the additional
control, conditioning and diagnostic circuitries that could integrate into the main functional block.

However, one interesting fact is, in parallel with academic research efforts, there are AFE (Analog Front End) chips with improved functionalities commercially produced by leading semiconductor manufacturers. (Sun et al., 2000) describes a HV US linear amplifier IC with sine wave generator. But its operating frequency is only 4.4MHz which is on the low end for most medical imaging applications, although 180Vpk-pk is a good voltage swing range. WURMADS uses a state of the art US pulser with integrated TX/RX switch (STHV748, STMicroelectronics, Geneva, Switzerland). IC has a very small foot-print with integrated 4-channel drivers. Use of this hybrid function IC greatly reduced the physical area requirement for the electronics assemblies.
Figure 3.18 shows the 8-channel TX/RX configuration of WURMADS. Instead of using dedicated LNA/VGA and ADC, all the low voltage outputs are connected together to form a single bus. However this configuration diminishes the ability to individual receive beam-forming (inability distinguish individual echo profiles) as it only gives the summation of the voltages. However if sequential excitation is adopted, above problem can be avoided. If all the transducers are excited together, summation of the echo profiles can be expected (3.6).
\[ Output(V) = \sum_{n=1}^{8} V_{Ch(n)} \] (3.6)

where \( n \) is the number of channels in the array.

### 3.6.9 Scan Cycle

As shown in Figure. 3.18, TX/RX switch is individually controllable. This enables several transmit-receive configurations to be implemented. A configuration in which only a single transducer is excited and all others are in received mode, provides the echoes received by each element. However it is not possible to identify the channel as it is a voltage sum of the channels. This demands a scheme that provide information about which channel received the echo profile during the receive phase. WURMADS has predominantly two scanning sequences.

- Sequential
- Simultaneous

For the experiments in this thesis, we adopted the sequential scanning mode. In this mode, each transducer element is excited sequentially one after the other with a fixed time delay to received the reflected echo profile. The delay between each excitation can be very small and governed by the scanning depth. To complete one full scan cycle of 8 channels will only take less than 1mS. Once the scanning is completed, it produces a data matrix of 1000 × 8. This can also be called as an image, although resolution is limited as WURMADS has only active 8 channels.

The second scanning mode excites all the transducers simultaneously or with phasing delays. Adding delays to the channels is also called transmit beam forming (Hassan, 2014) (Hedrick et al., 2005). Due to the quasi-radial arrangement, naturally channels are focussed towards the center of the forearm. Hence the beam-forming is not utilized in WURMADS. In simultaneous excitation, the received signals are summed to form a single composite signal of all 8 channels (3.6). If the bands are worn with true quasi-radial arrangement, there is a chance of receiving the pulses excited from ventral side by the transducers on the dorsal side and vice-versa. However we did not implement this scanning mode for the data collection.
3.7 Summary

This chapter presented the electronic and control architecture of WURMADS with unique Quasi-Radial wearable transducer array construction. The unique design of WURMADS addresses the noted hardware related problems in the literature (Castellini et al., 2014) with regards to SMG. There were no researches conducted to resolve portability, wearability and practicality problems using US in forearm muscle activity detection context. In dexterous forearm/hand prosthesis control, it is vitally important to have easy wearable and portable sensory system. The previous systems used in the SMG context are based on standard medical US systems and probes to capture images. In this chapter we presented a novel wearable concept together with efficient electronic controller to facilitate the stated requirements. Generally it was a challenge to get WURMADS working to meet the research objectives. The working model that used in data collection sessions is a result of several design iterations. Cost wise, the transducers are the most expensive component that costed us nearly £100 each. For the controller electronics and the PCB only costed around £400, which is a very good price for a portable US system with a few unique features. The system can also be used in continuing researches in Sonomyography.
Chapter 4

Evaluation of the Hardware

4.1 Introduction

This section details the experiments carried out to evaluate performances and commission WURMADS prior to use on human subjects. Ultrasound quality assurance is important for medical imaging systems to maintain the appropriate standards. However, WURMADS doesn’t fall into the category that carries out medical imaging for clinical diagnosis purposes.

A statement of diagnostic safety of Ultrasound can be found in Appendix. A.

In WURMADS, each transducer produces A-Mode output signal during each scan cycle. To construct an image, A-Mode signals from each transducer is concatenated to produce a matrix, that contain 1000 observations per channel. For the data analysis, we used MATLAB R21012b with $1000 \times 8$ matrices as primary input.

For US equipment quality assurance purposes, uniquely fabricated tissue-mimicking test phantoms are used. Practically for high-density arrays, imaging test phantoms are a vital element to evaluate the spatial resolution of the scans and sensitivity. Similar to other test phantoms used in different imaging techniques such as CT, x-ray, etc, US phantoms are made of a mixture of echogenic and anechoic materials to mimic actual human bone-tissue densities. For the testing of WURMADS, we employed a water bath test phantom which is a cheaper yet efficient alternative to expensive phantoms (Blaivas et al., 2004).

In this study, following points are evaluated to confirm the WURMADS performances.

- Single element mathematical analysis
- Single element radiation pattern
4.2 Ultrasound Physics

This section investigates the theoretical background on US transmission and reception with regards to WURMADS. As stated previously WURMARDS uses custom designed transducers. Technical details can be found in Chapter 3. US wave propagation depends on the mass, density and its intrinsic elastic properties (Laugier, 2011). In linear propagation, no mass is displaced as the wave propagates from point to another point and the medium stays stationary. Biological tissues are normally considered as viscoelastic solids. Soft-tissue has density of 1060kg/m$^3$ which is very close to the density of water (999kg/m$^3$). This is one reason to use water based coupling medium between transducers and the skin for maximum energy transfer (This is also true for water test phantoms). However in reality ultrasound propagation is considered linear with smaller wave amplitudes. As the amplitude increases, propagation is considered non-linear. It can result waveform distortions and the generation of harmonics of the fundamental frequency. It is said that non-linear phase occurs in the near-field region. Acoustic impedance is the resistance of the medium for the transmission of sound. This is also directly proportional to the amount of acoustic energy reflection if the incident wave is perpendicular to the surface. Transducers used in the wearable bands in this study are geometrically placed to make a perpendicular contact with the skin.

For perpendicular incidence US waves 4.1, the reflection coefficient is given by, (Hedrick et al., 2005)

$$\alpha_r = \left( \frac{Z_2 - Z_1}{Z_2 + Z_1} \right)^2$$

(4.1)

where $\alpha_r$ is the reflection coefficient, $Z_1$ and $Z_2$ are the acoustic impedances of medium 1 and 2 respectively. Multiplying this by 100 gives the percentage of reflection.

$$\%R = \left( \frac{Z_2 - Z_1}{Z_2 + Z_1} \right)^2 \times 100$$

(4.2)

Similarly transmission coefficient ($\alpha_t$) is given by

$$\alpha_t = \frac{4Z_2Z_1}{(Z_2 + Z_1)^2}$$

(4.3)

Useful transmission percentage is 100 minus the percentage reflection. ($\%T = 100 - \%R$)
\[
\%T = \frac{4Z_2Z_1}{(Z_2 + Z_1)^2} \times 100
\]  

(4.4)

**Figure 4.1:** Reflection and transmission caused by the US incident wave. Acoustic impedances of the mediums determine the amount of reflected energies

The following Table 4.1 shows approximate impedances of selected bodily organs.

<table>
<thead>
<tr>
<th>Material</th>
<th>Acoustic Impedance (kg/m(^2)/s) (\times 10^6)</th>
<th>Velocity (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air</td>
<td>0.0004</td>
<td>330</td>
</tr>
<tr>
<td>Fat</td>
<td>1.38</td>
<td>1450</td>
</tr>
<tr>
<td>Water</td>
<td>1.48</td>
<td>1480</td>
</tr>
<tr>
<td>Blood</td>
<td>1.61</td>
<td>1570</td>
</tr>
<tr>
<td>Kidney</td>
<td>1.62</td>
<td>1560</td>
</tr>
<tr>
<td>Liver</td>
<td>1.65</td>
<td>1550</td>
</tr>
<tr>
<td>Muscle</td>
<td>1.70</td>
<td>1580</td>
</tr>
<tr>
<td>Soft tissue</td>
<td>1.63</td>
<td>1540</td>
</tr>
<tr>
<td>Bone</td>
<td>7.80</td>
<td>3500</td>
</tr>
<tr>
<td>PZT(Crystal)</td>
<td>30</td>
<td>3870</td>
</tr>
</tbody>
</table>

**Table 4.1:** Acoustic impedances of various organs and substances

Percentage of reflection 4.2 from different material boundaries is given in the Table 4.2.

<table>
<thead>
<tr>
<th>Interface</th>
<th>Reflection percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soft tissue - air</td>
<td>99.9</td>
</tr>
<tr>
<td>Soft tissue - lung</td>
<td>52</td>
</tr>
<tr>
<td>Soft tissue - bone</td>
<td>43</td>
</tr>
<tr>
<td>Fat - liver</td>
<td>0.78</td>
</tr>
<tr>
<td>Soft tissue - fat</td>
<td>0.69</td>
</tr>
<tr>
<td>Soft tissue - muscle</td>
<td>0.04</td>
</tr>
<tr>
<td>Water - Lucite</td>
<td>13</td>
</tr>
<tr>
<td>Caster oil - soft tissue</td>
<td>0.43</td>
</tr>
</tbody>
</table>

**Table 4.2:** Percentage of reflection from different boundaries
From the tables 4.2 and 4.1, it is evident that smaller the acoustic impedance difference between the two layers, smaller the reflection percentage. For example soft-tissue interfaces with air and bone have higher energy reflection percentages and highly echogenic.

### 4.2.1 Attenuation in Tissue

Signal attenuation constitutes the effects of both absorption and scattering in the characterization of amplitude reduction as US signals travels through a medium. It is also described by an exponential function dependent on the medium composition, distance travelled and the frequency. As the frequency increased, the reduction in strength of the US signals is prominent. Experimental results presented in Chapter 3 during the frequency selection exercise also evident this. As a rule of thumb, the depth of penetration becomes less as the frequency is increased (Hedrick et al., 2005).

Factors contributing to attenuation of US signal may include,

- Absorption
- Reflection
- Scattering
- Refraction
- Diffraction
- Interference
- Divergence

A mathematical description of absorption is given by the following equation 4.5. At a particular location within a monochromatic US plane wave field (z), the changes of instantaneous pressure (p) with time, exhibit oscillatory behaviour, in which the maximum deviation is designated as the maximum amplitude pressure ($p_o$). The initial acoustic pressure at the surface ($p_{max}$) decreases as the US wave travels through a homogeneous medium. This can be presented in an exponential function 4.5. (Hedrick et al., 2005) (Gibbs et al., 2009).

$$p_o = p_{max}e^{-\alpha z} \quad (4.5)$$
Similarly attenuation can also be described by an exponential function. The form of equation 4.5 remains unchanged but the absorption coefficient is replaced by the attenuation coefficient \( a \).

\[
p_o = p_{\text{max}} e^{-az}
\]  

(4.6)

The attenuation coefficient \( a \) is the sum of scattering coefficient \( a_s \) and the absorption coefficient \( \alpha \).

\[
a = a_s + \alpha
\]  

(4.7)

The coefficients quantify the respective losses in peak amplitude pressure per unit length from absorption \( (\alpha) \), scattering \( (a_s) \) and both processes together \( (a) \). Napier (Np) per cm is the standard unit for these coefficients.

US intensity is a physical parameter that describes the amount of energy transmitting through a unit cross-sectional area per second. Potential biological effects of using US are directly linked to the applied intensity. In medical US, the effects are well documented and studied. The British Medical Ultrasound Society’s (BMUS) safety statement can be found in Appendix (A) that explains the safety margins for use of US on human subjects.

The time averaged US intensity is given in 4.8, which decreases exponentially with distance from the transducer.

\[
I = I_{\text{max}} e^{-\mu z}
\]  

(4.8)

where \( I \) is the intensity at the POI (Point of Interest), \( I_{\text{max}} \) is the initial intensity at the transducer, \( z \) is the distance travelled by the beam and \( \mu \) is the intensity attenuation coefficient. The intensity of an US signal is proportional to the square of the pressure amplitude. Therefore the intensity attenuation coefficient is related to the amplitude attenuation coefficient which is given by 4.9.

\[
\mu = 2a
\]  

(4.9)

The units of intensity are Jules/cm\(^2\)/s or Watts/cm\(^2\). This energy is considered to be the kinetic energy of particles that accelerated and decelerated by the pressure wave produced by the transducer aperture.
4.3 Single-Element Transducer Model: Wave-Front Dynamics Evaluation

In this section characteristics of the 1-Dimensional 5MHz single-element transducers used in WURMADS are investigated. US transducers are mostly based on theoretical models. There are three widely used models in the literature (M et al., 2003).

- KLM
- Mason
- Redwood

Other models require the knowledge of the materials and physical properties of the transducer. In this study we only focused on the KLM model for the transducer simulation (Spicci and Cati, 2011) (M et al., 2003).

In Figure. 4.2, KLM model has two parts, which are mechanical and electrical. Mechanical section is considered as the piezoelectric ceramic, matching layers and the backing material. The parameters for the piezoelectric transducer are given as follows.

\[
\begin{align*}
C_0 &= \frac{\varepsilon_{33} A}{d} \\
Z_0 &= \rho v A \\
X_1 &= \frac{h_{33}}{\omega^2 Z_0} \sin \left( \frac{\omega d}{v} \right) \\
\phi &= \frac{\omega Z_0}{2h_{33}} \frac{1}{\sin \left( \frac{\omega d}{2\pi} \right)}
\end{align*}
\] (4.10)

where \(\varepsilon_{33}\) is the permittivity constant under no applied voltage to the ceramic crystal, \(\rho\) is the density, \(h_{33}\) is the piezoelectric pressure constant, \(v\) is propagation speed of the sound wave, \(Z_0 = \) acoustic impedance, \(\omega = \) angular frequency, \(A\) and \(d\) are the area and thickness of the piezo-ceramic respectively.

The acoustic (4.11) and electrical (4.12 on page 78) system of the model can be described as follows (Wu and Chen, 1999).
Figure 4.2: Equivalent circuit for the transducer (WURMADS). Cable impedance is 50Ω. Bottom image (B) shows the KLM model for a transducer with thickness "d". (C) depicts the actual transducer model of WURMADS. $Z_b$ and $Z_f$ are the acoustic impedances of backing material and biological medium (skin). $Z_1$ is the matching layer.

Characteristic Impedance $Z_a = \rho v_a A_a$  

Phase Velocity $v_a = \sqrt{\frac{C_e}{\rho}}$  

Mass $\rho A_a = \frac{Z_a}{v_a}$  

Compliance $\frac{1}{\rho v_a A_a v_a} = \frac{1}{\rho A_a \left\{ \frac{C_e}{\rho} \right\} }$  

Loss factor $R' = \omega \rho A_a \delta$  

$$\text{Characteristics Impedance } Z_a = \rho v_a A_a$$  

$$\text{Phase Velocity } v_a = \sqrt{\frac{C_e}{\rho}}$$  

$$\text{Mass } \rho A_a = \frac{Z_a}{v_a}$$  

$$\text{Compliance} \quad \frac{1}{\rho v_a A_a v_a} = \frac{1}{\rho A_a \left\{ \frac{C_e}{\rho} \right\} }$$  

$$\text{Loss factor } R' = \omega \rho A_a \delta$$
4.3.1 KLM Simulation Results

The single element transducer used in WURMADS has been simulated with available parameters. We used "Biosono" KLM transducer simulator for the evaluation. Minimum number of pulses produced by WURMADS is 5, which is a hardware limitation and cannot be further reduce without software upgrade.

Parameters for the KLM simulation given above (Figure. 4.3) can be found in Appendix. E. Linear and phase array are the two transducer excitation modes in medical imaging (Dusa et al., 2014). In linear mode, individual elements or a group of elements in an array are excited where as in phased array mode, all the elements are excited with delays added in to it. This delaying (also called beam-forming) helps to focus the beam to an area of interest (AOI). In some systems where apodization is executed in hardware, center transducers of the excitation group received higher energies than the ones near the corners. Phased array mode is also used to steer the beam to the required direction with/without focusing electronically. The latter method requires an array element with $\lambda/2$ spacing of the centre frequency (Hedrick et al., 2005). This construction is crucial in order to produce constructive interferences by the individual element wave fronts. However WURMADS uses a larger diameter transducers in quasi-radial construction hence unable to adopt the $\lambda/2$ approach that helps to implement electronic beam-steering and focusing. Different types of transducer array configurations used in the context are listed below.

- Linear switched array or one-dimensional arrays - Consists of a large number of elements in a line, generally 64-256 elements.

- Linear phased arrays - Contains fewer elements than the one dimensional array but $\lambda/2$ rule is respected in order to steer and focus the beam by employing appropriate excitation delays.
Two dimensional arrays - The problem of inability scan a plane that perpendicular with 1D linear arrays can be alleviated by 2D arrays. Therefore by using a 2D array, it is possible to steer and focus on a 2D plane electronically. The notable disadvantage is the electronic complexity, that requires dedicated drives and delay controllers to each and every transducer element in the array. However modern medical US systems use 2D arrays as they give better lateral and axial resolution.

Annular array transducers - Annular transducers are composed of a set of concentric circular elements where electronic focusing allows symmetrical focusing in all
direction. However beam steering requires a mechanical rotation.

Out of above listed configurations, we can conclude that the quasi-radial array in WUR-MADS is closest to the linear array in behaviour. However quasi-radial construction gives a curvilinear appearance. Frame rate of WURMADS is adjustable electronically in real-time. However in offline data logging modes, maximum frame rate is limited to 4.3. Theoretical frame rate can be expressed by the following equation.

$$ R_f = \frac{c}{2ND} \quad (4.13) $$

where $c$ is the speed of sound, $N$ and $D$ are the number of beams and depth of image respectively. If post-processing and transmission latencies kept out of the equation, WURMADS is capable of achieving 2400 frames/sec, although in reality, considering the initial image processing latencies, this is difficult to achieve. During the testing phase, WURMADS achieved 100+ frame rates.

### 4.4 Wave Propagation: Huygens Principle

Huygens principle, models sound as spherical waves emitting from a source. Each point on the emitted wave front is considered as a source of secondary spherical wavelets with suitable amplitude and phase. In order to evaluate the beam profile, we have to assume that the transducer’s surface consists of infinite number of point sources and a spherical wave is emitted by each point source. In this section circular transducer (WURMADS) field pattern and scattering is analysed by Rayleigh-Sommerfeld diffraction formula. This formula can be interpreted in terms of the Huygens principle of secondary sources and can accurately estimate the field at any given spatial point. For these approximations, the transducer is considered immersed in a medium (fluid), which is homogeneous, continuous and of infinite extent to make a uniform coupling at the source surface (Farjat and Etcheverry, 2007).

Let radius of the transducer be $a$, point source $\vec{r}_1 = (x_1, y_1, 0)$ and any spatial point $\vec{r}_o = (x_o, y_o, z_o)$ on the observation plane (Figure. 4.4).

$$ \tilde{\Phi}(r_0, \omega) = \frac{1}{i\lambda} \int_{-\pi}^{\pi} \tilde{\Phi}(\vec{r}_1, \omega) \frac{e^{ikr_z}}{r_{01}} \frac{1}{r_{01}^2} r_1 dr_1 d\phi_1 $$

$$ + \frac{1}{2\pi} \int_{0}^{a} \int_{-\pi}^{\pi} \tilde{\Phi}(\vec{r}_1, \omega) \frac{e^{ikr_z}}{r_{01}^3} r_1 dr_1 d\phi_1 \quad (4.14) $$
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Figure 4.4: Coordinates for the equation 4.14. The fields are calculated at spatial point \( r_o \) on the observation plane

Low and high frequency contributions are presented by the first and second terms of the equation 4.14, where,

\[
\omega = \text{Angular frequency}, \quad \lambda = \text{wavelength}, \quad i = \sqrt{-1}
\]

\[
k = \text{wave number}, \quad k = \frac{2\pi}{\lambda}
\]

\( r_{o1} \) - Distance between the transducer plane \( (z = 0) \) and parallel observation plane \( r_o \) is located. This distance can be calculated by the following equation.

\[
r_{o1} = \sqrt{(x_o - x_1)^2 + (y_o - y_1)^2 + z^2} \quad (4.15)
\]

Similarly,

\[
\tilde{\Phi}(\overrightarrow{r_o}, \omega) - \text{The Fourier transform of the field } \tilde{\Phi}(\overrightarrow{r_o}, t) \text{ at point } \overrightarrow{r_o}.
\]

\[
\tilde{\Phi}(\overrightarrow{r_1}, \omega) - \text{The Fourier transform of a complex aperture weighting function } \tilde{\Phi}(\overrightarrow{r_1}, t) \text{ at a point on the transducer } \overrightarrow{r_1}.
\]

It should be noted that in practice, due to double integral Rayleigh-Sommerfeld diffraction formula (4.14) is difficult to calculate. As \( r_{o1} \) goes beyond \( \frac{\lambda}{2\pi} \), the second term goes towards zero. Therefore 4.14 can be rewritten as,

\[
\tilde{\Phi}(r_0, \omega) = \frac{1}{i\lambda} \int_0^a \int_{-\pi}^{\pi} \tilde{\Phi}(\overrightarrow{r_1}, \omega) e^{i k r_{o1} z} \frac{1}{r_{o1}^2} r_{o1} dr_1 d\phi_1 \quad (4.16)
\]
4.5 Radiation pattern: $y_o = 0$

When the observed point is in-line with the transducer, the distance between the source and the field point under observation simplifies. As depicted in Figure. 4.4,

\[ x_1 = r_1 \cos(\phi_1) \quad (4.17) \]
\[ y_1 = r_1 \sin(\phi_1) \quad (4.18) \]

Therefore equation 4.15 can be rewritten as,

\[ r_{o1} = z \sqrt{1 + \frac{r_1^2}{z^2} + \frac{x_o^2}{z^2} - \frac{2x_or_1 \cos(\phi_1)}{z^2}} \quad (4.19) \]

With the Fresnel approximation (H and E, 1993), $r_{o1}$ in denominators and phase equation (4.14), can be approximated by,

\[ r_{o1} \approx z \]

and

\[ r_{o1} \approx z + \frac{r_1^2}{2z} + \frac{1}{i} - \frac{x_or_1 \cos(\phi_1)}{z} \quad (4.21) \]

Substitution of this to 4.14 gives the field from a circular transducer at an observation point where $y_o = 0$ gives,

\[
\tilde{\Phi}(r_0, \omega) = \frac{1}{i\lambda} e^{ik\left(z + \frac{r_1^2}{2z}\right)} \int_0^a \tilde{\phi}_1(r_1, \omega) e^{\frac{ix_1^2}{2z}} \times \left( \int_{-\pi}^{\pi} e^{-\frac{i\omega r_1 \cos(\phi_1)}{z}} d\phi_1 \right) r_1 dr_1 \quad (4.22)
\]

The Bessel beam is considered as one of many solutions for the homogeneous wave equations that gives solutions for the waves in space rather than time. Bessel beams are considered diffraction free and do not diverge during transmission (Durnin, 1987), (Nowack, 2012), (Mitri, 2014). Two integrals in 4.22 is simplified by employing Bessel function of the first kind of zeroth order ($J_0(z)$).

\[
J_0(z) = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{iz \cos \phi} d\phi \quad (4.23)
\]

Substitution of 4.23 to 4.22 gives,
\[
\Phi(r_0, \omega) = \frac{2\pi e^{ik(z+\frac{z^2}{2\pi})a}}{i\lambda \cdot z} \int_0^a \tilde{\phi}_1(r_1, \omega) e^{\frac{ikr_1^2}{2z}} \times (J_0 \left( \frac{kx_0r_1}{z} \right))r_1dr_1 \quad (4.24)
\]

WURMADS US transducers are unfocused in which the Fresnel zone has an uniform beam diameter. The pressure fields for an unfocussed transducer surface is equally weighted which can be written as,

\[
\tilde{\Phi}(r_1, \omega) \equiv 1 \quad (4.25)
\]

Substituting 4.25 to 4.24 gives,

\[
\tilde{\Phi}(r_0, \omega) = \frac{2\pi e^{ik(z+\frac{z^2}{2\pi})a}}{i\lambda \cdot z} \int_0^a e^{\frac{ikr_1^2}{2z}} \times (J_0 \left( \frac{kx_0r_1}{z} \right))r_1dr_1 \quad (4.26)
\]

Far Field or Fraunhofer zone (which is explained in following sections) occurs where \(r_{o1} \approx z\) and \(z \gg \frac{kr_1^2}{2}\). Then the quadratic phase factor in 4.26 is one over the aperture, \(e^{\frac{ikr_1^2}{2z}} \approx 1\). Then 4.26 becomes,

\[
\tilde{\Phi}(r_0, \omega) = \frac{2\pi e^{ik(z+\frac{z^2}{2\pi})a}}{i\lambda \cdot z} \int_0^a (J_0 \left( \frac{kx_0r_1}{z} \right))r_1dr_1 \quad (4.27)
\]

Now considering the relationship of \(\int zJ_0(z)dz = zJ_1(z)\) where \(J_1(z)\) is a first order Bessel function of the first kind gives the result,

\[
\tilde{\Phi}(r_0, \omega) = \frac{ka^2}{iz} e^{ik(z+\frac{z^2}{2\pi})} \left( \frac{2J_1 \left( \frac{kx_0a}{z} \right)}{\frac{kx_0}{z}} \right) \quad (4.28)
\]

Jinc or sombrero function (as it looks like a sombrero hat) is the 2D polar coordinates analog of the sinc function which also can define through Bessel function of the first kind as give above.

\[
jinc(X) = \frac{2(J_1(\pi X))}{\pi X} \quad (4.29)
\]

Now Jinc function can be substituted in 4.28,

\[
\tilde{\Phi}(r_0, \omega) = \frac{ka^2}{iz} e^{ik(z+\frac{z^2}{2\pi})} \left( jinc \left( \frac{2ax_0}{\lambda z} \right) \right) \quad (4.30)
\]
So the beam intensity of unfocused transducer becomes,

\[ |\tilde{\Phi}(r_0, \omega)| = \left( \frac{ka^2}{iz} \right)^2 \left( jinc^2 \left( \frac{2ax_o}{\lambda z} \right) \right) \]  

(4.31)

The first zero of \( |\tilde{\Phi}(r_0, \omega)| \) along the radius is at,

\[ x_o = 1.22 \left( \frac{\lambda z}{2a} \right) \]  

(4.32)

\( Jinc(x) \) for the circular transducer where \( X = \frac{2ax_o}{\lambda z} \) can be depicted as shown in Figure 4.5.

![Figure 4.5: Jinc(x) plot depicting unfocused transducer field. Y - Non-normalized amplitude in linear scale, X = \( \frac{2ax_o}{\lambda z} \).](image)

**4.5.1 Near and Far Fields**

In ideal scenarios, transmitted US energy beam should be cylindrical. However due to beam dispersion when travelling through a medium, cylindrical beam, changes to conical in most cases. Wave generation from the ceramic disk can be mathematically modelled as the sum of the waves from a large number of point sources. This was first proposed by a Dutch physicist Christiaan Huygens (as above), who stated that each point on an
advancing wave front may be thought of as a point source that launches a new spherical wave, and that the resulting unified wave front is the sum of all of these individual spherical waves.

In WURMADS quasi-radial transducer array, single element transducers have overall diameter of 10mm and approximate piezoelectric ceramic diameter of 9mm. The range of transmitted energy from a transducer falls into two regions called near and far fields. In the near field (N) (also known as Fresnel zone), acoustic energy presence can be high but suffers from constructive and destructive interference, resulting fluctuations and non-uniformity of the beam. It also follows a converging beam profile due to constructive and destructive interferences. Harmonic generation in near-field is minimum compared to the far-field. The region beyond the near-field is called far-field (Fraunhofer zone) where the energy is contained in a conical distribution and more stable. The maximum acoustic pressure occurs at the end of the near-field where the beam is also the narrowest. According to the literature near-field is considered favourable for high lateral resolution as the beam is less diverged. Smaller transducers have a very short Fresnel zone. The near field of the WURMADS transducer can be evaluated by the following equation (4.33) (Hedrick et al., 2005).

\[ N = \frac{D^2 f}{4V} = \frac{0.009^2 \times 5 \times 10^6}{4 \times 1540} = 65mm \]

where \( D \) is the diameter of the transducer, \( f \) and \( V \) are the frequency and velocity in the medium respectively.

In practice, having a larger transducers not always beneficial to obtain higher resolution in medical imaging. Therefore US probe manufacturers use arrays of smaller piezoelectric ceramics and excite multiple neighbouring units to produce a sufficient wave front with appropriate near field (Fresnel zone). Since WURMADS has comparatively larger diameter (≈ 10mm), it has a longer Fresnel zone giving a more focussed beam. This is favourable in forearm applications as the forearm muscles are relatively smaller compared to the muscles in other limbs. Therefore higher axial and lateral resolution can be achieved without having to use tightly packed large element arrays.

In far-field, divergence angle of the beam is mathematically expressed by the following equation.

\[ \sin \theta = 1.22 \frac{\lambda}{D} \]
where $\lambda$ is the wavelength of the transmitted US pulses. From the equation 4.35 we can estimate the divergence angle of the transducers used in WURMADS.

$$
\sin \theta = 1.22 \times \frac{0.000308}{0.009} = 0.041751
$$

$$
\theta = 2.39^\circ
$$

$\lambda$ was estimated by taking the speed of sound in soft-tissue as $1540 \text{ms}^{-1}$. However the target depth of WURMADS is 3-4cm, which lies within the Fresnel zone and divergence is improbable.

### 4.5.2 Q-Factor

In US transducers Q-Factor (Quality factor) is measured as the ratio between fundamental frequency and bandwidth. Higher the Q factor better the transducer. According to manufacturer’s data, WURMADS transducers have a bandwidth of 56.1% (Table. 3.1 on page 49). This gives the quality factor of,

$$
Q = \frac{\text{Resonant frequency}}{\text{Bandwidth}} = \frac{5000000}{2800000} = 1.7
$$

High Q transducers retain energy in the crystal and loses very little in each cycle. Low Q transducers on the other hand produce a short pulse following each excitation as most
of the energy is lost from the crystal and converted to acoustic energy. In general medical diagnostic probes use low Q transducers with Q values of approximately 2. High Q Transducers (> 700) used in continuous wave applications ((Hedrick et al., 2005)). Therefore Q value of 1.7 in our application can be considered as intermediate for imaging applications and the WURMADS is technically limited to produce only 5 excitation pulses.

4.6 Experiments: Single Element Spatial Resolution Analysis

The objective of this section is to measure the axial resolution of the transducers we have used. For this experiment, custom designed water bath phantom is used. Generally commercially available US tissue mimicking test phantoms cost well over £1000. This forced us to use an alternative solution to test WURMADS and its transducer performances. Water bath test phantoms are widely used to calibrate and test purposes at medical US frequencies (Chenga et al., 2014), (Blaivas et al., 2004). For the resolution analysis, we designed three experiments that are carried out in a water bath phantom. Axial resolutions of single and dual echo profiles were analysed for thickness measurements.

4.6.1 Axial Resolution: 1 Layer

Axial resolution is also known as azimuthal resolution, the resolution parallel to the US beam. It is defined by the minimum distance that the reflected beam can differentiate between emitter and the reflector. Generally this resolution is considered as half the spatial pulse length ($\lambda/2$). However this resolution can only be achieved if one pulse is transmitted from the transducers (Alexander and Swanevelder, 2011). In the case of WURMADS, the resolution can be lower as the shortest burst contains 5 pulses, which is also the spatial pulse length. This is a constriction of the beam-forming integrated circuit that supplied by the manufacturer (Texas Instruments).

For this test we used a water bath phantom with 1mm plastic sheet as the reflector at a distance to be measured from the transducer. The transducer was fully submerged in the water bath allowing close to 100% energy transfer. Spatial Pulse Length (SPL) in this experiment can be considered as,
Chapter 4. Evaluation of the Hardware

\[ SPL = \left( \frac{v}{f} \right) \times 5 = \left( \frac{1482}{5 \times 10^6} \right) \times 5 = 0.001482m \] (4.37)

where \( v \) and \( f \) are the speed of sound in water at 20\(^\circ\)C and the pulse frequency respectively. According to 4.37, WURMADS can achieve 1.4mm of axial resolution, which is comparable with other medical US systems.

For the experiments in this section, the following set up (Figure. 4.7) is used to measure the axial resolutions.

\[ d \]

**Figure 4.7:** Experimental set up to measure the axial resolution in a water bath phantom. A single transducer is used to emit and receive 5 pulse burst. A plastic sheet is used as the reflector.

The distance \( d \) is known and measured using a vernier calliper with high precision. The transducer was integrated in the acoustic absorption form (Appendix. F) in order to prevent and absorb possible structural vibrations. The transducer was excited by \( \pm 50V \) pulse train and received waveform was recorded in a PC. Table 4.3 contains the estimated and observed distances and mean error in millimetres.

The results revealed that the mean error is less than 1.4mm, which is the estimated spatial resolution for the WURMADS (4.37). However the given results are based on the mean distance over a few frames, which might have positively affected the final
results. Anyhow, the results suggest that the axial resolution of WURMADS obtained from a single barrier is within the theoretical spatial resolution and fit for the purpose.

Average percentage error can be denoted as, (Gibbs et al., 2009)

\[ \text{Percentage Error(\%)} = \frac{\text{Actual Measurement} - \text{Observed Measurement}}{\text{Actual Measurement}} \]  

<table>
<thead>
<tr>
<th>Observed</th>
<th>Actual</th>
<th>Error (mm)</th>
<th>(%)</th>
</tr>
</thead>
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<td>10</td>
<td>-1</td>
<td>10</td>
</tr>
<tr>
<td>13</td>
<td>12.5</td>
<td>-0.5</td>
<td>4</td>
</tr>
<tr>
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<td>15</td>
<td>0.3</td>
<td>2</td>
</tr>
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<td>17.5</td>
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<td>1</td>
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<td>2.222222</td>
</tr>
<tr>
<td>24</td>
<td>25</td>
<td>1</td>
<td>4</td>
</tr>
</tbody>
</table>

\begin{align*}
\text{Mean} & = 0.642857143 \\
\text{SD} & = 0.350509833 \\
\end{align*}

Table 4.3: Axial resolution test results 1: The reflector is set at the given observed distances

4.6.2 Axial Resolution: 2 Layer

In this experiment, two layers are used to mimic boundaries of a muscles or two layers. The distance between the layers were measured. Two 1mm plastic plates were used as mentioned in the previous experiment in the same water tank phantom arrangement, Figure. 4.7 [Appendix. F]. A single channel echo profile is depicted in Figure. 4.8. In this experiment, first plastic layer was kept fixed while the other moved by a known distance. Actual and observed results were compared and the results are given in Table. 4.4.

<table>
<thead>
<tr>
<th>Observed</th>
<th>Actual</th>
<th>Error (mm)</th>
<th>(%)</th>
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<tbody>
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<td>10</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>12</td>
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<td>4</td>
</tr>
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<td>14</td>
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<td>6.666667</td>
</tr>
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</tr>
<tr>
<td>24</td>
<td>25</td>
<td>1</td>
<td>4</td>
</tr>
</tbody>
</table>

\begin{align*}
\text{Mean} & = 0.857142857 \\
\text{SD} & = 0.243975018 \\
\end{align*}

Table 4.4: Axial resolution test results of two boundaries
4.6.3 Apodization and Modes of Operation

Apodization is a beam focusing method to reduce side lobes of US beams that focussed towards a specific region. In transmitting mode this is achieved by exciting the elements non-uniformly in order to control the intensity profile across the beam. Side lobes amplitude and focal zone can be extended by exciting innermost elements more than the outer elements. However, this practice widens the main lobe as a side effect. Apodization is largely discussed in US context, however it is effective in multi-element transducers. In practice this is achieved by decreasing the excitation power of the outermost transducers in an array. In WURMADS, since the transducers are placed far apart and due to the larger aperture, apodization is largely ineffective.

WURMADS hardware platform is capable of facilitating several modes of operations. The modes of operation defines the transducer exciting patterns and receive configuration. Number of active channels can be changed from 1 to 8. Pulse trigger sequence and delays are individually programmable. However those delays are useful only for beam-forming requirements. By default WURMADS has 0 transmit delays between the channels.

4.7 Summary

Evaluation of the hardware performances and a theoretical overview is presented. WURMADS transducer and hardware performances measured by employing a water bath phantom. Huygens model is applicable to the WURMADS transducer as a single element circular aperture. From the calculations, near-field of the transducer is 65mm,
which is longer than the depth of interest (DOI) to acquire data from the forearm. The angle of divergence is 2.39° with Q (Quality) factor of 1.7 which is comparable with standard medical probes. Evidence has been provided regarding the spatial resolution using A-Mode US analysis (Hoskins et al., 2010)(Chapter 6). Lateral resolution is not considered here as it lies beyond the scope of the application. Axial resolution is within the acceptable range. The average calculated errors were 0.64±0.35 (4.01%) and 0.85±0.24 (5.37%) for ranging and thickness measurement respectively (Table. 4.4). In standard US machines image size is governed by the settings and focused ROI. Generally, according to US quality assurance practices errors beyond 5% must be reinvestigated. It should be noted the applications of WURMADS does not require the exact dimensions of muscles or morphology as for the clinical use. A stable jitter free A-Mode signal is sufficient to monitor muscle activities. The evidence presented in this chapter proved it is feasible.
Chapter 5

Methodology for Experimentation

5.1 Introduction

In this section WURMADS application and experiment design on both able and disable subjects are discussed. A new term introduced, Fatigue-Less Maximum Isotonic Contraction (FLMIC), and justified along with experimental evidence. Detailed description of the employed amputee subjects are given along with datasets and segmentation approaches. As the primary method of gesture recognition Pearson Cross-Correlation (CC) is used. Preliminary results are obtained and presented in the latter part of this chapter to evaluate the amputee dataset. In this thesis, application of the methods are focused on the amputee subjects. The forearm muscle physiology of amputees is different to able counterpart depending on the nature of the amputation. Trans-radial and wrist amputees were primarily employed in this study (Figure. 5.3 on page 104). Nowadays, most prostheses come with all five digit flexion/extension capabilities. However some popular prosthesis such as i-Limb cannot facilitate certain movement but its capable of pronation/supination. Digit control is more useful in day to day activities than wrist flexion/extension. Forearm muscle compartment contains three layers (Figure. 5.1), superficial (closest to the skin), middle and deeper layers. For digit flexions, primarily Flexor digitorum profundus/superficialis muscles on the anterior side are used. These are deeper and middle layer muscles, when sEMG is used, electrical potentials need to travel through superficial muscle layers to be observed. Anatomically small(pinky) finger flexion is associated with the ring finger.

Table 5.1 on page 94 lists the forearm muscle/muscle groups that are responsible for hand gestures and manoeuvres.
Figure 5.1: Anterior and posterior compartments of muscles in the forearm. Three layers of muscles are present (superficial, middle and deep) to facilitate palm/hand, wrist and digit control and forearm pronation/supination gestures. Author holds no rights for the image. Source: http://humananatomybody.info/
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Table 5.1: Muscle or muscle groups responsible for digit flexion/extension

<table>
<thead>
<tr>
<th>Digit/action</th>
<th>Flexor</th>
<th>Extensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thumb</td>
<td>Flexor pollicis longus</td>
<td>Extensor pollicis longus</td>
</tr>
<tr>
<td>Index</td>
<td>Flexor digitorum superficialis</td>
<td>Extensor digitorum</td>
</tr>
<tr>
<td>Ring</td>
<td>Flexor digitorum profundus</td>
<td>Extensor Digiti Minimi</td>
</tr>
<tr>
<td>Small</td>
<td>Flexor carpi radialis/ulnaris</td>
<td>Extensor carpi radialis longus/brevis</td>
</tr>
<tr>
<td>Wrist</td>
<td>All above</td>
<td>All above</td>
</tr>
<tr>
<td>Fist hand</td>
<td>Pronator Teres/Quadratus</td>
<td>Supinator</td>
</tr>
</tbody>
</table>

Table 5.1: Muscle or muscle groups responsible for digit flexion/extension

5.2 Anatomy of Human Forearm and Types of Contractions

This study is focused on the most suitable types of forearm muscles contractions required to control a dexterous prostheses. Fundamentally there are three types of muscle contractions.

1. Isotonic (Meaning same tension)
2. Isometric (Meaning same distance)
3. Isokinetic (Meaning same speed)

Isotonic contractions are the focus of this study to support the hypotheses. As it is the most prevalent type of contraction in trans-radial amputees without imposing fatigue on muscles. This type of contractions are normally allow people to move about generally. There are two variations of Isotonic contractions, Concentric and Eccentric. In concentric contractions muscle fibres shorten as tension increases, such as lifting a weight. In eccentric contractions, contractile force generated by the muscle is smaller than the opposing force, causing muscle to stretch, for example lowering a load. On the other hand isometric contractions occur when the muscle maintain the same length as tension increases. A good example is holding a glass in hand against the gravity. In such instance, increase in gripping force does not change shape of the muscles.
5.2.1 Mechanism of Muscle Fatigue

Muscle fatigue occurs due to prolong and repetitive muscle activity. Fatigue reduces the EMG frequency domain and increases the amplitude of the signal. Fatigue takes place in two domains, physiologically and neurologically (Al-Mulla et al., 2011). Physiological manifestation of fatigue occurs due to the exhaustion of the metabolic reserves in the contracting muscle. As the amount of wastes increase in the muscle, build up of lactic acid takes place which decreases the amount of glycogen or glucose. This negatively impact the contractile properties. Neuromuscular fatigue mechanism occurs due to changes in both the nerve system and the muscle causing it to fatigue. Motor Unit (MU) is considered as a single motor neuron that located in the spinal code and the muscular fibres that innervated by the neuron. When an MU fires, the brain transmits an electrical impulse, known as Action Potential (AP), down the neuron to the neuromuscular junction, where motor neuron meets the muscle fibre, which is also known as motor endplate. Collection of these MUAP can be measured as EMG. When muscle fatigue progresses, recruitment of MU increases affecting the EMG (Amplitude) and frequency spectrum.

5.3 Fatigue-Less Maximum Isotonic Contraction (FLMIC)

In the literature Maximum Voluntary Isometric Contraction (MVIC) is widely discussed. However there is no relevant literature related to isotonic contraction in amputees. As previously mentioned, studies focused on dynamic/isotonic free (no tension) muscle contractions and fatigue relationships are least explored (Rodrigues et al., 2009) (KENT-BRAUN et al., 2013). Fatigue can also affect the classification accuracies in prosthesis control, a phenomenon which requires more attention (Herrmann and Buchenrieder, 2009). During the initial investigations of the research, the author observed that to produce significant and usable sEMG signals, the targeted muscles must be activated towards to tetanic region. This arguably induces fatigue and diminishes the performances. Therefore this phenomenon must be further investigated, which is an essential factor in prosthesis control. This problem is also cited by many researchers (Winters and Woo, 2012)(pp 363-365) (Park and S.G., 1993). Generally muscle fatigue occurs sooner in isometric contractions compared to isotonic as it requires motor units to maintain the activation to retain the force (Goodwin, 2012)(pp460).

It is vital to understand that digit flexion from resting posture to posture where the finger tip barely touches the palm doesn’t require vast amount of MU to be activated. However, importantly, majority of morphological changes take place during this phase which is extremely useful for SMG. Due
to a fewer MU activations for the contraction with minimum effort, there is minimum detectable sEMG. Experimentally we observed this with many able subjects informally. In order to detect further EMG activities, subject must contract the muscle further. When this happens in healthy subjects, finger flexions is restricted by the palm, while the muscles are minimally changing its length. Change in length ($\Delta l$) is correlated to the distance that finger tip dips into the palm, assuming that there is no elasticity in tendons. During this phase muscles will further activate to overcome the resistance, resulting more MUs to be recruited and visibly stiffening the muscle or muscle groups affiliated to this action.

We failed to cite any literature detailing these physiological phenomenon relevant to this discussion. However advanced books on medical skeletal muscle physiology and other publications contain relevant information written for different aspects contextually. Therefore the author considered further detailing these phenomenon lies out of the scope of this thesis. However the reader can easily observe this with their own forearm.

**Method:** Flex the middle finger to the point it barely touches the palm as explained earlier, the reader can now use the other hand, grab from the finger tip and try to flex/extend the fingers of the first hand (except the middle finger which is already flexed). Notice that they move without any restrictions and freely. Now further flex the middle finger to seat on the palm firmly. Notice the travel will be only a few millimetres, through the skin. Now again using the other hand, try to flex/extend the fingers. The reader will notice that they are stiffened although only the middle finger is consciously flexed! Importantly this phase is the most useful in sEMG detection as it produces increased amplitude and wider frequency spectrum.

Activating a muscle towards the tetanic region also recruits further MUs. Close examination of muscle architectures presented in Figure. 5.1 on page 93, reveals that several digit tendons originated from a single muscle, for example flexor digitorum profundus and flexor digitorum superficialis. This suggests that lower activation potentials will produce minimum tension to flex the finger without activating all the muscle fibres, but locally. This will not fatigue the muscles, but responsible for larger morphological changes. This is the foundation for the argument constructed in this chapter which concludes as muscles do not required to fully activated for SMG, but the minimum activation is sufficient within the region where greatest morphological changes take place. In practice, careful placement of electrodes cannot be followed as electrodes are pre-installed in the prosthesis socket. It is also not feasible to use adhesive surface electrodes every time in sEMG. In most studies, the maximum voluntary contraction (MVC) of muscles is used for evaluate the muscle strengths. MVC involves the muscles to reach its tetanic phase where fatigue is prominent. Therefore in applications where SMG is used, MVC is not necessary, but enough contraction to induce morphological changes is adequate.
Therefore the author would like to propose the contraction type prevalent in amputee subjects and relevant for this study as **Fatigue-less Maximum Isotonic Contraction (FLMIC)**.

Justification argument of FLMIC, is formulated based on three hypotheses as given below,

- Majority of morphological changes occur during low-level isotonic contractions
- The phase in which most morphological changes occur, exhibit lowest sEMG activity
- This phase is the least fatigue inducing

The difficulty of finding related literature that covers all the above areas related to prosthesis control, motivated the author to design the following experiments.

### 5.4 Evidence to Support the Hypotheses

The following experiment is designed to investigate previously mentioned hypotheses. We employed 4 healthy individuals, Age 30-35, mean weight of 65±5K and mean forearm circumference of 21cm. None of the subjects had any history of muscular disorder. The experiment consisted of two phases. The initial phase covered the first two hypotheses and the second phase covered the third, which is the fatigue evaluation.

#### 5.4.1 Experiment Protocol;

**Phase 1: sEMG RMS and Morphological Change Evaluation**

To collect SMG data, WURMADS is used with only 3 transducers (smaller ring). To capture enough muscle activities experimentally we found that three channels are sufficient. The reader can recall the online gesture recognition demonstration video produced by the author. That experiment consists of three US transducers which is enough to recognize > 6 gestures (Hettiarachchi). To capture sEMG, we utilized SHIELD-EKG-EMG bio-feedback shied developed by OLIMEX Ltd, Plovdiv, Bulgaria. SHIELD EMG is an Arduino compatible system, however we modified the circuit to suit our data collection procedure. The system is single channel that gives an analog output which is sampled at 1KHz by an external microcontroller. The microcontroller (PIC16LF1519, Microchip Inc, Arizona, USA) transmits the digital output in real-time to the PC.

A visual stimulus on a PC screen was used to guide the flexion levels. The subjects were
sat comfortably and placed their right forearm on the table with supine posture. Three US transducer band was mounted on the midsection of the forearm. For the sEMG, two wearable electrodes were placed next to the transducer band towards the elbow where we observed a significant EMG activities for the intended gestures. The electrodes were placed longitudinally where the flexor muscles are concentrated. Before the placement of the sEMG electrodes, skin of each subjects was cleaned and applied ordinary skin moisturisers to enhance the conductivity. We were also cautious about not to spread US gel and make contact with sEMG electrodes which can adversely affect the readings. Initially sEMG channel was corrupted by the SMG pulse excitation (Due to RF Fields). Later we removed the corrupted segments from the dataset. Data recording of both SMG and sEMG was synchronized with insignificant latency.

In this phase subjects were asked to perform two levels of contraction as per the stimulus. During the first level, four digits, except thumb, were flexed to the point where the finger tips were barely touching the hypothenar and thenar regions of the palm. The posture was maintained for 10 seconds and then the digits were flexed further to reach MVC. Both postures were maintained for 10 seconds to capture enough SMG and sEMG data. Five repetitions were performed.

5.4.2 Phase 2: Fatigue Analysis

Objective of this phase is to measure the sEMG amplitude variation (increase) due to muscle fatigue from rapid flexion/extension of digits. This analysis was executed in three phases.

- Recording of sEMG signals at MVC - (To measure energy and frequency spectrum at the beginning)

- Rapid flexion/extension of the four fingers nearly 100 times to FLMIC

- Repetition of the first step above.

Flexion/extension of four digits rapidly to maximum Isotonic contraction helped to measure the changes of amplitude and frequency spectrum of the recorded sEMG signals. Importantly subjects were asked not to produce tension in the muscles or strain during the flexion of digits that barely touched the palm (FLMIC). Generally the level of flexion is identical to the first stage of phase 1. Open hand posture is considered as the initial position for the above tests. For the second phase in which the fatigue is evaluated, SMG data was not captured for analysis.
5.4.3 Methodology

To measure the degree of morphological changes during the two stages of flexion in phase 1, we employed the cross-correlation method. Three templates were created by taking the means of initial, FLMIC and MVC postures. Let three templates be matrices of $1000 \times 3$, $M_I$, $M_F$ and $M_M$. Hence the degree of muscle deformation for two stages were measure as follows.

$$\Delta S_1 = 1 - (M_I \ast M_F)$$
$$\Delta S_2 = 1 - (M_I \ast M_M)$$

where $\Delta S_1$ and $\Delta S_2$ are the differences in correlation coefficients between resting and two stages of flexions. Window size for the sEMG signals is set as 10 seconds. In phase 1, two postures were maintained for 10 seconds to capture enough SMG and EMG data. Hence sEMG acquired during this period must have a stable amplitude characteristics.

5.4.4 Results and Discussion

<table>
<thead>
<tr>
<th>Case</th>
<th>Correlation</th>
<th>Sub 1</th>
<th>Sub 2</th>
<th>Sub 3</th>
<th>Sub 4</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resting - to - FLMIC (A)</td>
<td>0.2762</td>
<td>0.1478</td>
<td>0.4193</td>
<td>0.5099</td>
<td></td>
<td>0.3383</td>
<td>0.159326</td>
</tr>
<tr>
<td>Resting - to - MVC (B)</td>
<td>0.4277</td>
<td>0.2543</td>
<td>0.3698</td>
<td>0.3952</td>
<td></td>
<td>0.36175</td>
<td>0.075451</td>
</tr>
<tr>
<td>FLMIC - to - MVC</td>
<td>0.3822</td>
<td>0.4919</td>
<td>0.5283</td>
<td>0.6771</td>
<td></td>
<td>0.519875</td>
<td>0.12183</td>
</tr>
<tr>
<td>Resting (Training - test)</td>
<td>0.5897</td>
<td>0.9912</td>
<td>0.9858</td>
<td>0.9975</td>
<td></td>
<td>0.99115</td>
<td>0.005043</td>
</tr>
<tr>
<td>Change in coefficient($\Delta r$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resting - to - FLMIC ($\Delta S_1$)</td>
<td>0.7135</td>
<td>0.8434</td>
<td>0.5065</td>
<td>0.483</td>
<td></td>
<td>0.65265</td>
<td>0.157712</td>
</tr>
<tr>
<td>Resting - to - MVC ($\Delta S_2$)</td>
<td>0.562</td>
<td>0.7369</td>
<td>0.616</td>
<td>0.6027</td>
<td></td>
<td>0.6254</td>
<td>0.075258</td>
</tr>
<tr>
<td>Change A - to - B ($\Delta C$)</td>
<td>0.1515</td>
<td>0.1065</td>
<td>-0.0495</td>
<td>-0.1147</td>
<td></td>
<td>0.02345</td>
<td>0.126097</td>
</tr>
</tbody>
</table>

Table 5.2: Phase 1: Deformation at different stages of contraction (Averaged window)

Table 5.2 gives an analysis of the graphical representations in Figure. 5.2. The regions shown in three colors are the regions of interest (ROI) during window sampling. X axis represents the number of frames acquired during the task by each subjects. It is a fixed value as they were following a graphic stimulus as explained earlier. During the resting period, spans from 0-50 approximately, has a smaller window in which the frames are used to generate training template. The rest are the test frames contained the frames from two levels of contractions. The signal (black) shows the correlation coefficients, when resting posture template cross-correlated with each frame in the dataset. The overall deformation during the FLMIC low-level flexion is evident. In average 42.5% ($r^2$) change is observed. However further flexion to 100% MVC only produced a change
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Figure 5.2: Phase 1: Morphological deformation analysis using cross-correlation. Analysis windows are ≤ 10s

...of 1.1%. One of the important observations was the first two subjects displayed positive morphological change in which the template biased towards the resting posture template. As per the hypothesis, sEMG average amplitude values must also be analysed.

Table 5.3 depicts the EMG RMS amplitude readings for two flexions including the resting posture. Preliminary results show that there is a clear increase in amplitude at 100% MVC. Notably, in average, only a 5.15% of sEMG activity was observed during FLMIC flexion. However a larger increase (73.63%) in sEMG activity was observed at 100% MVC compared to FLMIC. This is a significant increase compared to actual morphological change took place in Figure 5.2 and Table 5.2 on page 99.

For the fatigue analysis, sEMG signal sampled at 1KHz, Fast Fourier Analysed (FFT) to
measure the largest frequency component present, before and after the vigorous flexions that only performed within the FLMIC region. At MVC, the highest frequency component of four subjects spanned from 75-100Hz. However, the expected fatigue induced frequency shift towards the lower spectrum could not be observed and inconclusive.

Contrary to literature where it says that the fatigue reduces the frequency with time, we observed minimum frequency shift in this experiment (Table. 5.4). However from the results we can conclude that the fatigue did not take place during the rapid contractions of the four digits in FLMIC region. In addition none of the participants complained of any fatigue related discomfort or pain following the session.

### 5.4.5 Justification of the Hypotheses

- Majority morphological changes occur during low-level isotonic contractions

Results shown in Figure. 5.2 on page 100 and Table. 5.4 revealed that the highest morphological change has taken place from resting to FLMIC flexion which is
42.5%. In the phase from FLMIC to MVC resulted only 1.1% of muscle deformation with respect to resting posture template. Although first two subjects at MVC, exhibited a small reversal of the deformation towards the resting posture.

- The phase in which the most morphological changes took place also demonstrated low surface EMG activity

Based on the single channel sEMG analysis during the four digit flexion, we can categorically prove that FLMIC phase produced the least amount of sEMG signals. The results show that, it only produced 5.15% of the saturation voltage. If it was measured against the voltage at MVC, the change is 8.3%.

- FLMIC is the least fatigue inducing phase

Vigorous isotonic flexion/extensions of the four digits 100 times showed no indication to suggest that the muscle fatigue has taken place. All four subjects demonstrated no frequency shift before and after the task at MVC.

As a conclusion, we have presented the evidence to support three hypotheses made earlier regarding the Fatigue-Less Maximum Isotonic Contraction (FLMIC). We would like to argue that this type of contractions can be found in trans-radial amputees and it can be adopted to control prostheses. Importantly, inducement of muscle fatigue can be minimized as majority of the morphological changes can be observed within the low-level FLMIC contraction phase.

Guo has done a similar study to ours with a single element standalone transducer (Guo et al., 2008a,b, 2009a). They measured the muscle deformation and root mean square signal against wrist extension angle. They observed a linear relationship that agrees with our findings upto a certain extend. However the differences between myoelectric and morphological changes during wrist extension can differ to digit flexions. Wrist extension involves several superficial muscle groups (extensor carpi ulnaris, extensor digitorum and extensor carpi radialis brevis). Based on the observations during wrist extension/flexion, sEMG generation can be higher than the digit flexion and with similar finger manoeuvres. Although we observed a similar pattern to the above study by Guo. Further investigation is required to confirm the facts with regard to the author’s findings in this chapter.
5.5 Amputees Employed in the Research

Isometric contraction model cannot be considered valid in the cases of amputees as mentioned in previous chapters. From the examinations of amputees revealed that most forearm amputees were capable of energizing the muscles that are relevant to a digit flexion/extension as prior to the amputation. This is an important fact to hypothesize that the forearm muscle contraction of trans-radial amputees are isotonic with minimum resistance. Wrist amputees in the group revealed that they have no resistance to the tendon movements hence allowing them to perform full contraction of the muscles. However some amputees, whom with removed or dissected muscles reported that they can still activate the muscles but a slight resistance is present. This may be a result of the nature of the amputation. All the subjects did not report of any pain beyond moderate (i.e. beyond 3-10, in 0-10 pain scale). However all the subjects were reported moderate pain when asked to contract the muscles further into the isometric region (Beyond FLMIC).

5.5.1 Levels of Amputation of the Subjects

Amputees selection process were taken place in Sri Lanka where a high number of war related amputees are present. Out of 11 subjects we examined, only 10 were approved for the data collection. All 10 subjects were ex-military soldiers who lost their limbs mostly by improvised explosive devices (IED). All amputations were taken place from 2007-2009. Two subjects were both hand amputees. (≤75Kg,male, 25 - 55 of age, average forearm circumference of 23cm)

Figure 5.3 depicts the amputated limbs of the subjects. Subject number 11 was rejected as there were not enough muscles to contribute significant morphological changes. All the other subjects were able to activate most of the remaining muscles. Surprisingly all the selected 10 subjects were able to activate muscles comfortably that are required for digit flexion and extension. The remaining length of the forearm was thoroughly inspected in order to confirm the multiple muscle activities. It will not be much helpful if just one muscle is working as it can only generate a single feature morphologically.

5.5.2 Healthy Subjects

For the experiments with healthy subjects, we employed 3 intact female and 4 male individuals (Based in the UK), (≤75Kg,male, 28-36 of age, average forearm circumference of 22cm), and with their consent. The data captured from healthy subjects were used in chapters 5, 6 and 7.
5.5.3 Visual Stimulus and Data Recorder

In supervised training and gesture execution, a visual stimulus is widely used in many previous studies. For example, (Castellini and Gonzalez, 2013), (Castellini et al., 2012), (Gonzalez and ClaudioCastellini, 2013), etc used visual stimulus as ground truth for the synchronous data recording. (Zheng et al., 2006) however used an audible guide as the
stimulus. This study employed a similar approach by displaying a graphical stimulus to guide the muscle activations and relaxations.

**Figure 5.4:** A - Visual Stimulus to Synchronize the gestures, B - Main software GUI with controls to handle the process depicted in Fig.5.5
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The stimulus is simple yet effective (Figure. 5.4). The blue color bar rises and falls to a predefined speed. The subjects should follow the bar that should be proportional to 0% - 100% MVC. Prior to data recording, subjects were trained adequately to satisfy the experiment necessities. The stimulus and the data recorder were activated simultaneously so that the recordings will have minimum delays and discrepancies.

Figure 5.5: Data recording procedure. Software manager is a PC running application

Figure 5.5 on page 106 shows the data recording process during the data collection. Software manager is a PC running application developed by the author (Windows XP and above) with a graphical user interface (GUI). Ethernet connection is dedicated for the incoming data packets from WURMADS hardware. Accelerometer circuit is also designed by the author which has its own processor to read all the axes and transmit data to the PC at 1KSPS. WURMADS and accelerometer (angle sensor) are continually streaming the data to the PC once initialized and buffered. However the data will not
be saved until the user triggers/enables the session. The following steps were respected prior to each data collection session.

1. Placement of the wearable US rings and accelerometer where they can provide the clearest signals. Specially in the case of accelerometer, orientation is paramount in order to get the maximum swing against gravity. Therefore one of the axes should be parallel to the ground.

2. Once Ethernet and accelerometer (USB) is connected to the computer, main software is activated. At this point data is sampled/acquired but won’t be saved.

3. By analysing the A-Mode US signals displayed on a separate window, it is possible to adjust the rings to enhance the signal clarity (optional).

4. To save the files, directory information is given to the GUI and initialize the set up (Figure. 5.5: B on page 106)

5. Once above steps have been followed, it is possible to enable the data collection

The recoding software will produce a text file for each frame received from WURMADS. This text file contains eight columns of data, each representing a US channel. There are 1000 observations per each channel, giving us 8000 data points per frame. In off-line data collection mode, WURMADS collect nearly 5 Frames/second. A typical session lasted for 2.5 minutes, producing 1200 frames. On arrival of each frame, accelerometer X, Y and Z values were collected as well. As previously mentioned, accelerometer is sampled 1000 times/second and the data is readily available in the input buffer.

5.6 Dataset Structure

Figure 5.6 depicts the dataset structure. We obtained four datasets from both able and disabled subjects. (University Ethics committee reviewed and authorised the proceedings). DB1 is obtained from 10 trans-radial amputees as detailed above.

Each dataset is comprehended by actual angular and stimulus data that synchronised with US frames denoted by 'A'. The data collection process is controlled by the user interface (Figure. 5.4 on page 105). Chapters 5, 6 and 7 are relied upon the datasets DB1/4, DB1 and DB2/3 respectively. In addition to those four datasets, WURMADS hardware testing dataset(DBT) was collected by using an US water bath test phantom. DB4 is used in chapter 5 to justify the FLMIC, SMG and sEMG relationship. This dataset is based on 4 male healthy individuals that contains stimulus, SMG and sEMG data.
5.7 Analysis of Data

Off-line analysis of data is carried out by MATLAB (2012a, Mathwork Inc, USA). The collected amputee dataset in Sri Lanka was named as DB1. DB1 was later segmented by acquiring the frame indexes at resting and MVC (Figure 5.7).
The segmentation acquired the frame indices at segments A and B and concatenated to form vectors $A_c$ and $B_h$ respectively. The dynamic segments were used (from indices array $A_c$) in Chapter 6 for the proportional control analysis.
5.8 PART 2: Evaluation with Cross-Correlation Method

It is important to note that, compared to EMG signals, A-mode US signals has distinct differences.

- Depending on the muscle fatigue level, frequency spectrum of the signals vary, whereas US signal has a fixed median frequency which is not affected by the movements.

- When muscles are at rest, there is no EMG activities, resulting near-zero amplitude of RMS value of the signal. Since US sees the morphology of the muscles, a steady signal with a fixed pattern is continually produced which is not time varying.

- A-mode signal has a fixed sample (N) length compared to time series continuous EMG signals. In US, only the amplitude profile (envelope) change of the signal will take place.

- In multichannel systems, such as WURMADS, it is therefore logical to consider acquired signals at a given times is a 2D matrix which can also be considered as an image $([I]_{1000 \times 8})$. Image processing approaches may be suitable although the matrix size is $1000 \times 8$.

- Number of samples (N) in SMG signal are ratio-metrically proportional to the scan depth

Cross-correlation method is widely used in signal processing applications to evaluate similarity between two given signals (Adrin-Martnez et al., 2014) (Rao et al., 2014) (Luo et al., 2014). Another advantage is the ability to implement the algorithm on a Digital Signal Processor (DSP) with minimum memory and processing capabilities. This is beneficial in portable systems (Hettiarchchi). We evaluated the system for the first time by template based cross-correlation method between the training and test sets. For this experiment dataset DB1 (Amputee) is utilized to measure the performances. Eight gestures were executed by each subject:

- Five digit flexion/extensions
- Fist hand
- Wrist flexion/extension
- Forearm pronation/supination
Ten Tran-radial (below-elbow) amputee subjects (≤75Kg, male, 25 - 55 of age, average forearm circumference of 23cm) were employed. All the subjects were trauma related amputees (war casualties). Two subjects were below-elbow both hand amputees. Subjects were provided with adequate instructions and guidance prior to the sessions. We extensively trained each amputee to follow the graphical stimulus of the trajectory and speed to synchronize the flexions-extensions. Each of the subjects was sat comfortably in front of a table while relaxing their hands with supine position on the table. Close physical inspection of the subjects revealed that some were unable to satisfactorily activate certain muscles due to lengthy indolence. In such cases, we stimulated the muscles by simple exercises. We attached the two quasi-radial US sensor bands on the areas where we observed significant muscle activities for simple finger flexions-extensions on the ventral side of the forearm. We placed 5-transducer band closer to the elbow where the majority of undamaged muscles are mainly concentrated in order to extract more information. The second 3-transducer band was placed near the mid-section between the forearm dissection and the five-transducer band. Once the transducer bands were properly fastened on the forearm, the subjects were asked to perform the eight eight gestures listed above and repeated 20 times with ample amount of time in between them. As for the reference, graphical stimulus was displayed on a computer monitor in front of each subject to synchronize metronomically to the depicted trajectory and position in real-time. This helped us to time the session and capture finer details during the each transition as it taking place slowly.

5.8.1 Features

Contrary to sEMG, SMG has fewer features to work with. Unique markers such as frequency spectrum or power density spectrum (PDS) in sEMG, cannot be found in SMG due to its single fundamental frequency. Root mean square (RMS) amplitude of EMG signal is closely related to the muscle activity. In SMG, signal amplitude is a direct representation of the morphological structure underneath the transducer. It does not change when the hand is at rest. Movements of the muscles change its CSA (Cross Sectional Area) hence varying the positions of echogenic boundaries with respect to surface of the skin. In most cases reflected acoustic pulse’s amplitude does not change. During the experiments we noticed that, A-mode ultrasound signal amplitudes varied significantly but it was repeatable. In this investigation we used two features,

- Signal amplitude, overall pattern variations (Cross-correlation)
- Total acoustic energy per channel
Total energy is measured by taking the area under the Hilbert transformed signal envelope. Let the extracted envelope be \( f(t) \). The area can be obtained by,

\[
\text{Area} = \int_{1}^{n} f(t)dt
\]  

(5.2)

where \( n \) is the number of observations, which is normally 1000 samples and fixed.

### 5.8.2 Template Based Correlation

This process contains three phases, template preparation (based on the signal envelope), cross-correlation with each image in the dataset and evaluating the recognition rate. Matrix that contain eight channels are considered as an image in this study. Templates were prepared by taking the average of first five repetition. Then the templates were used to evaluate the correlation between each of the frames in the dataset and store the recognized gesture against its index.

Index extraction is based on the stimulus data which derives the flexion/extension curve. As per the graph (Figure. 5.8), gesture and resting position indices were extracted. The cross-correlation algorithm is given in 5.3.

\[
corr = \frac{n(\sum A_{tr}B_{tt}) - (\sum A_{tr})(\sum B_{tt})}{\sqrt{[n\sum A_{tr}^2 - (\sum A_{tr})^2][n\sum B_{tt}^2 - (\sum B_{tt})^2]}}
\]  

(5.3)

Let \( A \) and \( B \) are the training template and test images respectively. \( corr \) \( (r^2) \) is obtained for each test image in the dataset. Since there are eight gestures to be identified, each of the image in test data, cross-correlated with each of the eight templates. The gesture with the highest correlation is considered a match.

\[
ARR_{estimated} = [G_n \ N_i]_{n=1}^{n=8}
\]  

(5.4)

where \( G \) is the recognized gesture and \( N_i \) is the corresponding index for the \( n^{th} \) gesture. To evaluate the recognition rate, number of recognized gestures \( ARR \) is compared with the indices array \( ARR_{actual} \). The process is repeated for each gesture \( n = 1 \) to 8.

The mean recognition rate for each gesture was evaluated by using the error of actual and estimated gesture hits. It should be noted that the resting posture is also considered as a gesture in SMG. Contrary to sEMG, relaxed posture can still produce morphological echo patterns.
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Figure 5.8: Recognition rate evaluation methodology

\[
\text{Recognition rate} = \frac{\text{ARR}_{\text{estimated}}}{\text{ARR}_{\text{actual}}} \times 100\% \quad (5.5)
\]

5.9 Results

Figures. 5.9, 5.10 and 5.11 (on pages 114, 115 and 116) provide the results obtained from above calculations.

5.10 Summary

Mean results for all 10 subjects are presented in Figures. 5.9, 5.10, 5.11 on pages 114, 115 and 116. For gestures, highest recognition rate was achieved for subject 1, which are 100% for gestures and 97.92% (4.96)\{Percentage(SD)\}. In general for all 10 subjects who performed 8 gestures, demonstrated 97.9% (3.75) and 89.2% (7.7) gesture recognition rates for gesture and resting postures respectively. The results are comparable with the recent studies in the context. There are only a few studies that designed to recognize finger gestures using SMG (Gonzlez and ClaudioCastellini, 2013) (Sikdar et al., 2014). Wrist joint angle and SMG based on A-mode ultrasound, (Guo et al., 2008b) has demonstrated a linear relationship compared to EMG. RMS tracking
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Figure 5.9: Average recognition rates of 8 gestures. Two curves represent the gesture and relaxed postures.
Figure 5.10: Average deviation ($r$) of matched and unmatched gestures
Figure 5.11: Recognition rates obtained from both CC and AUC methods.
error for SMG was also lower than EMG. At the time of writing, Sikdar’s work (Sikdar et al., 2014) on recognizing five digit flexions remains the closest to this study where he obtained, classification accuracy of 98% for individual finger movements. However, the stated study is based on healthy subjects.

Dexterous control of prosthesis involves multiple gesture recognition beyond simple wrist/hand flexion/extensions. Simple gestures such as fist hand and thumb abduction are currently facilitated by commercial myoelectric based prostheses. Keeping a good enough margin between matched and unmatched gestures is paramount. Figure 5.10 on page 115 is the boxplot depicting matched/unmatched mean deviations. Subject 10 revealed the weakest gesture differentiation in average. The data used for this depiction (only CC) can be found in Appendix C.1. All subjects have a safe margin of $\Delta r = 0.35(0.046)$. This is a good margin considering the norm of $r \geq 0.8$ as good correlation and $r \leq 0.5$ as weaker correlation. The obtained margin is greater than the accepted margin. Figure 5.11 on page 116 depicts the overall results obtained from AUC and CC methods for gesture and resting postures. Although we observed some amplitude variation between the gestures, AUC method didn’t reveal satisfactory results.

In general AUC method gave us mean recognitions rates of 80.15%(8.3) and 60.95%(12.8) for gesture and resting postures respectively. This is compared to 97.9% (3.75) and 89.2% (7.7) for CC method. This result is comparable with the results obtained by (Sikdar et al., 2014), where they obtained $> 98$% classification accuracy with a standard medical US system.

We also observed that as the repetitions progress, there is a tendency to decrease overall correlation coefficient values. However the important feature is it is proportional to both gesture and resting postures. Therefore it didn’t affect the overall gesture recognition rate but only the coefficients reduced. This reduction in correlation is caused by the slippage of the transducers and overall movements of the quasi-radial rings. However the effect of the echo profile is proportional for gesture and resting postures, there will be minimum effect on the overall recognition rate. The conditions we had during the data collection sessions (DB1) in Sri Lankan ($> 30^{\circ}$ ambient temperature), may have contributed the small reduction in correlation due to coupling gel drying out. In average, for all subjects, percentage muscle deformation recorded was 12.6%. Interestingly this value is close to the flagship research of (Zheng et al., 2006) in which the reported percentage changes were 7.2 $\pm$ 3.7% for healthy and 9.5% (Approximately) for amputee subjects.
Chapter 6

Proportional Control Evaluation

6.1 Introduction

This chapter investigates the digit flexion prediction on amputees, based on a model derived from the features of time-series (M-Mode) 3-Dimensional US images. A statistical evaluation of gesture recognition capabilities is also investigated. We introduced quasi-radial sonomyography that facilitated by the Wearable Ultrasound Radial Muscle Activity Detection System (WURMADS) that previously presented. With the rapid advancement of robotic prosthesis over the recent years, an efficient Human Machine Interface (HMI) for proportional control of robotic hands was arisen to execute complex manoeuvres and in-hand object articulation. The methods that are proposed, potentially beneficial in fulfilling this requirement with quasi-radial sensor arrangement. Traditional non-invasive myoelectric detection strategy of Surface Electro Myography (sEMG), cannot reliably identify the deeper muscle activations in the forearm due to crosstalk and signal attenuation. It also suffers from signal degradation due to muscle fatigue and non-linearity. Low to medium frequency electrical impulses are barely detectable at the surface of the skin. This makes it difficult to distinguish the origin and isolate a certain gesture from another that uses a same set of muscles. However, modern robotic prosthesis are mainly rely on sEMG to control the manoeuvres (Matrone et al., 2012)(Al-Timemy et al., 2011). Due to these limitations, alternative methods such as Sonomyography is widely discussed in present day. 10 trans-radial forearm amputee subjects were employed in this study to capture data from supervised gestures. A recent study (Sikdar et al., 2014) proved that proportional control is feasible using relative change of US echogenicity. However this study utilized medical ultrasound probes that gave higher resolution images.
This study is consist of two sections in which we evaluated the digit angle by analysing the M-Mode echo-gradients and gesture recognition by supervised learning classification. The results suggest that proposed quasi-radial construction can be used to estimate the muscle deformation proportionally from resting position to MVC. By employing a generic model based approach we achieved $90.27\pm1.79\%$ prediction accuracy of digit flexion in average for 10% to 100% in deciles. The estimated synchronization error between the stimulus and the transitional phase from resting to MVC is $6.60\pm2.62\%$. In the second part of the chapter where individual digit flexion was analysed, classification accuracies of $90.25\%$ and $72.2\%$ for combined KNN (K-Nearest Neighbour) and cross-correlation (CC) were achieved. Also $87\%$, $71\%$ and $79\%$ was achieved respectively for KNN, Pearson’s cross-correlation and ensemble bagging classifications. The results suggests, the proposed CC-combined method with KNN classifier outperforms the others.

### 6.2 Proportional Control

Quantification of muscle contraction is a demanding challenge. Higher the degree of freedom of digits, it demands an efficient controller to make use of added functionalities. Surface EMG technology is incapable of satisfactorily determining the degree of muscle activation. Most everyday hand gestures require fine and smooth proportional control of the fingers such as holding a mug or picking up an egg. If the controller is unable to recognize the finer variations of the activation, the only possible interpretation and translation would be either 1 and 0, based on the simple threshold based rules. This is the common control strategy in sEMG based prostheses.

In this study, we address the notable gap in the context in detecting robust proportional signal to facilitate fine control by adopting the sonomyographic technique in M-mode.

### 6.3 Experimental set-up

For the data collection we used Wearable Ultrasound Radial Muscle Activity Detection System (WURMADS). The hardware comprises of the processing electronics and wearable ultrasound transducer rings that contain eight single-channel transducer elements. Contrary to bulky standards ultrasound probes and acquisition electronics, we designed WURMADS (Figure. 6.1) to be easily wearable and portable to facilitate practical prosthesis control. The transducer elements are purpose built to the specification we provided to the manufacturer, *Shenzhen Hurricane Tech.Co Ltd, China*.

Figure. 6.1 shows the experiment set-up. Bluetooth connectivity and i-Limb simulation were performed offline to translate the gestures.
Figure 6.1: WURMADS and its application (Offline; data collection with two transducer rings attached) The prosthesis is i-limb (Touch bionics Limited). The system is also capable of standalone online gesture recognition.

We employed 10 Tran-radial (below-elbow) amputee subjects (≤75Kg, male, 25 - 55 of age, average forearm circumference of 23cm). All subjects reported feel of the phantom limb with limited pain and ability to execute all five-digit flexions. Two subjects were below-elbow both hand amputees. Subjects were provided with adequate instructions and guidance prior to the sessions. We extensively trained each amputee to follow the graphical stimulus of the trajectory and speed to synchronize the flexions-extensions. Each of subjects was sat comfortably in front of a table while relaxing their hands with supine position on the table (Figure. 6.1). We attached the two quasi-radial US sensor bands on the areas where we observed significant muscle activities for simple finger flexions-extensions on the ventral side of the forearm. On subjects who sparsely have substantial forearm muscles left, we placed the bands on both dorsal and ventral sides,
perpendicular to the same cross-sectional plane. Once the transducer bands were properly fastened on the forearm, the subjects were asked to perform simple eight gestures repeated 20 times with ample amount of time in between each repetition. As for the reference, graphical stimulus was displayed on a computer monitor in front of each subject to synchronize metronomically to the depicted trajectory and position in real-time. This helped us to time the session and capture finer details during the each transition as it taking place slowly.

In this study, we only focused on the flexion curve to estimate the digit position. From 2 to 5 repetitions were considered as the training set and the rest as test data. First repetition data was omitted as it was allowed to settle the transducer and make coupling medium properly seated and distributed between skin and the transducer. In many occasions we observed that the very first repetition signal’s amplitude was significantly higher or distorted than the rest.

### 6.3.1 Gesture Mirroring

Trans-radial amputees employed in this study can only perform concentric and eccentric isotonic contraction without a visual feedback. However due to the nature of the amputation, some subjects reported a feeling of resistance for certain digit movements hence some fatigue was observed. Subjects were asked to mirror isotonic gestures on the healthy hand, where a 3-axis accelerometer was fixed. Limb mirroring is a trick to the visual system into believe that the phantom limb is moving. This also helps to induce kinaesthetic sensation in the phantom limb, if present, hence it perceived to move in the mirror. (Ramachandran et al. 1996.) The sensor collected the angular information while the gesture is being performed in order to correlate the echo variations with the true action. The sampling latency between accelerometer and US frames was negligible (<1mS). The following is the list of performed mirrored isotonic gestures -

1. Thumb abduction
2. Index finger flexion and extension
3. Middle finger flexion and extension
4. Ring finger flexion and extension
5. Small finger flexion and extension

The 3D accelerometer was fixed at the most appropriate location for each gesture to obtain the clearest and maximum axial angular deviation ($\Delta(x,y,z)$). In the case of both-hand amputees, the sensor was fixed to the remaining length of the mirrored limb. For
the data analysis, an algorithm is used to determine which channel causes the maximum angular deviation corresponding to 0 - MVC%.

Each image is an instantaneous depiction of the morphological structure in the forearm as seen from a radial. This is different to standard high resolution ultrasound imaging. However, this exercise is not focused on identifying specific muscles but the overall morphological changes that may help to extract features varying with time. Since there are two ultrasound rings, it helped to capture echoes from different regions of the forearm. Conventional medical US probes cannot achieve this as they are not wearable, covers a wider region on the forearm or mounted on the circumference of hand.

### 6.3.2 Filtering using Hilbert Transformation

The signals from each US channel of the system were rectified and the envelopes were extracted by employing Hilbert transformation (6.1). It is widely used to extract the envelope of an amplitude varying signal (Qiu et al., 2014a). It creates an analytic (complex) signal $x_c(t)$ of the input signal using the transformation whose real part is the original time-series signal and the imaginary part is the Hilbert transformation of the original.

$$x_c(t) = x_r(t) + jx_i(t)$$  \hspace{1cm} (6.1)

where $x_r(t) \in \mathbb{R}$. The envelope is equal to the magnitude of $x_c(t)$, which is given by,

$$e(t) = \sqrt{x_r(t)^2 + jx_i(t)^2}$$  \hspace{1cm} (6.2)

where $e(t)$ is the envelope of the input time-series.

For each set of gesture repetitions, there are 8 time-series images, where x and y-axes denotes the number of frames (time) and 1000 points of observations (echo samples), derived from A-mode ultrasound signal, which can clearly produce echoes from fat-muscle and muscle-bone interfaces (Shi et al., 2010b). Echo from each channel per frame was filtered of noise and arranged in a time series (Figure. 6.2 :B). For each gesture, we obtained US time-series images by concatenating individual US channel echo profiles. These images depict the axial displacement of the echoes during the gesture execution. However, some channels didn’t show significant echo pattern deformations, suggesting fewer muscle activities.
6.4 Feature Extraction and Localized Weighted Centre Method: P1

An assumption can be made that when digits flex, echogenic regions or peaks change their positions with respect to time axially. If this is true then the weighted centre of each frame with respect to time will provide the pattern of physical displacement of the tissue. However, the target depth may contain one or more muscle boundaries where multiple echoes may change antithetically hence affecting the weighted centre. Thereby we adopted a windowed tracking method (Zheng et al., 2006).
Echo peaks in the profile extracted by transducers represent muscle boundaries, tendons, bones or blood vessels. Depending on the placement of the transducer and the scanning depth, which is on average 35mm (WURMADS), a single channel could see one or more muscle boundaries or tendons. In B mode (medical) US images, peaks are presented as brighter regions. In ideal conditions, approximate numerical axial summation of peaks should remain unchanged, because thickness change of a muscle or shift of a tendon will only affect the peak locations due to internal structural changes, unless they move laterally away from the main US lobe. Tracking features such as cross-sectional deformation of an US image using conventional Mutual information Free Form Deformation algorithm (FFD) is not feasible (Chen et al., 2011b) due to speckle noise. In addition, the weighted centre of a complete US image cannot use as a reliable tracking parameter. For an instance, concentric contraction widens the muscle but weighted centre may remain unchanged axially. To solve this problem we tracked each peak individually with a window to extract the morphological change within the boundaries with respect to time. In this approach, we assumed that any single muscle echogenic boundary will not structurally deformed beyond the limits of the window (±8mm) from resting to MVC position.

The process of windowed weighted center signal extraction is shown in (Figure. 6.3). Each of the processors are explained in the following sections.

The image was filtered to reduce speckle noise along the time axis. Peak detection algorithm is employed to isolate the regions of most echogenic and to extract the depth coordinates, R(z), where z is the depth. Keeping the depth coordinate as the centre point, a band of data was extracted in which the equivalent soft-tissue depth of ±1cm (BW), assuming the maximum muscle movements were concentrated within that region (AOI = z±BW). For each peak depth coordinate, signals were extracted and stored as 2D matrices. (Figure. 6.4 on page 126).

One problem we faced was a notable jitter of sampled data. This is partly down to the speckle noise and ADC (Analog to Digital Converter) noise. In some instances the observation points lie way beyond the ROI (Region of Interest). The Kalman filter could be beneficial in this application to extract the signal however 3 dimensional nature of the image forced us to consider an alternative rule based approach. The rule states that if a data point lies beyond a predefined band, the point will be ignored and interpolated.

In the following stage, the extracted signals were filtered by a finite impulse response filter (FIR), without inducing delays to prevent possible synchronisation issues. For each morphological signal extracted from the time-series image (Figure. 6.4,A on 126), the frequency spectrum was obtained by employing Fast Fourier Transformation (FFT) to measure its apparent sinusoidal nature. We normalized the duration of the dataset
to 1 second; hence, it is possible to obtain gesture repetition frequency (defined by the stimulus) during the data collection. The obtained FFT values for each morphological m-mode signal from the time-series were enumerated for the highest energy concentration around 20Hz which is the known supervised repetition frequency when normalized to 1 second. The above process was repeated for each channel to obtain the clearest signal.
Changing muscle CSA or movements of tendons induces sinusoidal nature to the signal. This is evident in previous researches as well (Guo et al., 2008a). Gradients of the extracted sinusoidal signal ($E$) and the actual accelerometer based angle signal were extracted. Positive and negative gradient regions correspond to flexion and extension respectively. Theoretically, segments (n...n1) in positive gradient regions should coincide with actual angle signal’s gradients if and only if the subjects were mirroring the gesture on the healthy hand where the accelerometer was attached, chronologically. The speeds of flexion-extension were slow enough to acquire enough frames and sample points during the transitions. The phase in which the gradient of ($E$) is either positive or negative always considered a digit flexion or extension. Note that in some cases gradient can be negative. During a digit flexion, if the targeted muscle boundary or the tendon moved
towards the transducer, this phase is considered positive gradient. However, we cannot guarantee that the (E) is obtained from a boundary that always moving towards the transducer. This is solely depends on the winning signal following FFT enumeration as discussed in a previous section. This enumeration returns the signal with clearest repetitive characteristics.

6.4.1 Polynomial Regression and Training Curve Features

Assume positive gradient vectors (\(\nabla g\)) correspond to flexions. For each vector, we obtained the corresponding frame indexes \((F_1 - n)\). Using the indexes, the actual segments of the signal in the training set were extracted and averaged \((p_t)\). Features such as height and length of the vector \((p_t)\) were extracted.

In this study, we found that the curve \(p_t\) could always be mathematically expressed as the following polynomial regression (6.3). Further analysis revealed that, this is true for each subject and for all executed gestures. This is a unique observation. Therefore, the function given here is considered as the model for the digit contraction estimations in the following stages in this study.

\[
F(x) = -0.004x^3 + 0.19x^2 - 0.53x
\]  

(6.3)

where \(x : x \in \mathbb{R}, x = (1, 30)\)

![Figure 6.5: Derived polynomial model for flexion](image)

Figure 6.5: Derived polynomial model for flexion
In this step, granular deformation of the muscles were estimated. The limits of the generic model (6.3) differ from actual limits (height, width) of training curve \((p_t)\) and individual test vectors. For each gesture, the model (6.3) was resized to the height and length of \((p_t)\). Then the model with new limits was used to calculate the deciles in terms of depth of contraction \((y\text{-axis})\). 10 deciles \((T_t)\), where each deciles represent 1/10 of digit flexion between resting (0\%) and MVC(100\%) were recorded.

\[
T_t = Y_1 \ldots Y_{10} \tag{6.4}
\]

\(T_t\) was then kept as the training estimates. In order to estimate the prediction error based on the function (6.3) and deciles coordinates (6.4) for the test data, curve segments for each repetition in the set were obtained. Then as the next step actual depth coordinates of deciles during positive \(\nabla E\) were obtained (6.5) from the signal for each repetition. Each decile coordinates \((y)\) were interpolated for the span of the positive gradient as those may differ from the training coordinates.

\[
T_r(n) = y_{1n} \ldots y_{10n} \tag{6.5}
\]

where \(n\) is the repetition index. For test data, it is 6-20.

Once 10 decile predictions were estimated, it is cross examined with the deciles coordinates \((T_t)\) obtained by the training function (6.3). We applied euclidean distance model for the estimation (6.6).

\[
d(T_t, T_r(n)) = \sqrt{\sum_{i=1}^{n} (T_t - T_r)^2} \tag{6.6}
\]

where \(n\) is the repetition index, \(T_t\) and \(T_r\) are training and test estimates respectively. The prediction error as a percentage is calculated as follows.

\[
\text{error}\% = \left| \frac{\sum \text{diag}([d])}{n} \times \frac{1}{p_t(\text{len})} \right| \times 100 \tag{6.7}
\]

where \(p_t(\text{len})\) is the length of the training curve that deduced previously.

### 6.4.2 Correlation with Mirrored Angle Data

Synchronization of gesture and accelerometer data was paramount in this study as it dictates the accurate segmentation of the data for the analysis. Figure. 6.6 shows the
Figure 6.6: Flexion prediction error for 10 percentiles.
mean prediction error of 10 deciles for each of the gestures per subject. In this section, synchronization error is evaluated with respect to time. Ideally, frame indexes within the gradient should coincide with digit transitional period from rest to MVC position. However, it is unlikely that the subjects precisely timed the muscle flexion with mirroring on the healthy limb. There is no means of evaluating this as it is completely down to the subject to synchronize and there is no significant visual feedback from the amputated limb either. This measurement is a parameter to justify the results obtained above (Figure 6.6), if the error is said to be small. Smaller error suggests that the extracted features and the signal \(E\) from the US image, during the digit flexion phase are valid and in phase with the mirrored angle data \(A_{xyz}\) (on the healthy limb).

The velocity of digit movement \((V)\) can also be estimated. Steeper gradients correlate to faster digit movements against the known sampling frequency. Amplitude of the signal from training set gives the MVC, hence the axial displacement can be acquired. To calculate the digit speed, visual stimulus frequency is used as the datum to compare with. However, amputees do not give physical evidence of a digit displacement in reality, but can be measured my tracking the muscle movements with change in height \((y)\) of the signal \(E\) and frame rate (6.8).

\[
V = \frac{\Delta y}{T_{frame}} \tag{6.8}
\]

6.5 Statistical Gesture Recognition Evaluation: P2

In this section, we evaluated the gesture recognition and repeatability analysis of the quasi-radial architecture of sonomyography with WURMADS. For this study, we utilized the same dataset (DB1) of 10 hand trans-radial amputee subjects who performed five supervised gestures. The mean of first three repetitions out of 20, considered as the training set. Manual segmentation performed on the dataset for resting and 100% MVC positions, producing the frame indexes for the evaluation.

Method: The dataset DB1 was segmented to gesture and resting positions based on the mirrored hand accelerometer based angle data (Figure 6.9 on page 133). Contrary to part 1 of the chapter, in which the flexion depth was estimated by employing a model, transitional region’s (gradients) frames were omitted as this exercise is to only recognize gestures. Frame indexes at the gesture and rest positions were recorded from the dataset. The flowchart is depicted in (Figure 6.8 on page 132) detailing the process.

Hand gesture recognition was performed by KNN classification, cross-correlation and combined KNN and cross correlation methods for comparison. For each gesture, 8
training matrices \([m \times n]\) were produced where \(m = 1000\) and \(n = 8\). In the matrix, 8 columns are the channels and rows represent each data observation points. Prior to producing the matrix, channels were individually processed and the envelop is extracted (6.1, 6.2 on page 122) for further filtering.

**Figure 6.7**: Mean flexion prediction error vs actual synchronization error deduced from accelerometer data. X-axis denotes the subjects.
6.5.1 K - Nearest Neighbour Method

K-NN algorithm is a standard classification approach in identifying gestures (Sikdar et al., 2014). It is a widely used classification method in sEMG controllers. In this classification technique, the training vectors from all the gesture motions can be used as templates to measure the distance between the input test vectors. In our approach, 8 class labels were produced for each channel for a gesture in the training set. Test instances were classified based on the closest class appeared near to the training instances. In order to return a complete match, relevant test classes must be closest to the training classes in corresponding order. Later the classification performances were extracted as a coefficient that gives the similarity.

The classification was performed by using two distance metrics, Euclidean distance and Cosine similarity to compare the results. However the Euclidean distance demonstrated overall insignificant 0.01% of classification efficiency so we employed better distance metric.
6.5.2 Pearson Cross-correlation and Idle Channel Elimination

In image and signal processing, cross-correlation is widely employed to compare the similarity of two given signals (Shi et al., 2010a). In this exercise, we compared the training matrix $M_{tr}$ with test matrices $M_{tt}$ to evaluate the similarity. For a given gesture, not all the columns or echo profiles in training matrices change. We call them idle channels of that particular gesture since the morphological change observed was insignificant to make an impact on the final classifications. To feed this information to the combined-classification method (cross-correlation and K-NN[CC-KNN]), an enumeration was performed between training set’s rest and the MVC position matrices (for all gesture). This gave us the channels that showed minimum activity, so those channels were excluded from both training and test matrices.

6.5.3 Combining Cross-Correlation and K-NN Method with Channel Rejection

In this method, cross-correlation is used to identify active channels, restructure the training and test sets and then apply the K-NN classification ($k = 3$) and cross-correlation
to enhance the efficiency as explained above. This approach reduces the number of classification classes by removing idle channels from the matrices. To eliminate the docile channels, cross-correlation is employed. The initial position matrix ($M_{CLIP}$) is checked against the gesture position matrix ($M_{CLGP}$) to find the docile channels, eliminate and restructure. Those channel indexes were also recorded.

$$r = \frac{n(\sum M_{tr}M_{tt}) - (\sum M_{tr})(\sum M_{tt})}{\sqrt{n\sum M_{tr}^2 - (\sum M_{tr})^2}[n\sum M_{tt}^2 - (\sum M_{tt})^2]}$$  \hspace{1cm} (6.9)

The correlation coefficient $r$ between two matrices is given by (6.9) where $n$ is the number of elements. $M_{tr}$ and $M_{tt}$ are training and test matrices respectively.

Individual correlation coefficients for $n$ (channels) were binary filtered with a constant (threshold). This produces a matrix ($A_{tr}$) with valid active channel indexes. Similarly, active channels matrix ($A_{tt}$) for test matrices were produced to compare and decide whether to proceed or not in classification stage. The elimination process is given in Algorithm. 1 on page 136.

If recorded active channel indexes were a mismatch with test indexes after docile channel elimination, the classification was rejected. This is due to the fact that if the channels were different, there is no logical reason to proceed with classification and the match was set as 0%.

An example:

$$\begin{pmatrix} 1 \\ 0 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \\ 1 \end{pmatrix} = A_{tr} \hspace{1cm} \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 1 \end{pmatrix} = A_{tt}$$

If $A_{tt} \neq A_{tr}$, then classification will not be proceeded and considered a mismatch condition. However there is an exception for the condition, $A_{tr} \subseteq A_{tt}$.

The first two images of Figure. 6.10 depicts the combined KNN and cross-correlation methods with channel elimination.
Figure 6.10: Five digit gesture recognition using 1. Combined KNN. 2. Combined Cross-Correlation. 3. KNN. 4. Cross-Correlation. 5. Ensemble Bagging classification. The $y$ axis denotes training matrices that compared with.
Data: ROI, R(z,x)
Result: Classifier feed
initialization;
while $G \leq$ no.of training gestures do
  while $n \leq 8$ do
    $A_{tr}(n)(G) = M_{tr(i)}(n) \ast M_{tr(g)}(n)$;
    $A_{tt}(n)(G) = M_{tt(i)}(n) \ast M_{tt(g)}(n)$;
  end
end
normal loop;
while $G \leq$ no.of training gestures do
  while $n \leq 8$ do
    if $A_{tr}(G) \land A_{tt}(G) = True$ then
      Proceed with classification;
    else
      Unmatched gesture: Ignore;
    end
  end
end

Algorithm 1: Classification followed by channel elimination. Where $G$ is gesture ID. There are $G$ number of arrays of $A_{tr}$ and $A_{tt}$.

![Figure 6.11: Mean differences between matched and unmatched gestures](image)

6.6 Results and Discussion

The model based approach of flexion depth estimation proved that it is repeatable and can achieve $90.27 \pm 1.79\%$ prediction accuracy for 10 deciles (Figures.6.6, 6.7 on pages 129, 131). The structural changes observed in quasi-radial sonomyography provide reliable features to quantify the amount of muscle deformation. In healthy subjects, muscle deformation is linearly proportional to the isotonic contraction (Castellini et al., 2012). The results suggest that this is also valid for amputee subjects although the
model is polynomial in nature with a dominant linearity. The average synchronization error is only 6.60±2.62% suggesting that the visual stimulus and the physical muscle deformation caused by motor activations were highly correlated. Therefore the extracted signals from time-series images considered valid. Figure 6.7 on page 131 depicts the sync and prediction error for all subjects. In Figure 6.6 on page 129 it shows that in some cases the error has risen (upper whisker) considerably close to 50%. Presumably this resulted by partly activated the muscles below MVC. In G2, subject 5 has a very low prediction error although one of his repetitions did not satisfy MVC. However, this is one of the limitations as there is no means of reliable feedback to quantify the contraction of amputees. Subjects 3 and 9 (Figure 6.7 on page 131) exhibit higher error deviation for 4 gestures out of 5. Interestingly these two subjects were a both hand amputees who could not perform limb mirroring although the error is still in an acceptable range. As a conclusion, the results suggests that by employing our Quasi-radial hardware approach on amputees, it is feasible to implement proportional control of dexterous prostheses.

In the second part, gesture recognition was investigated for five digit flexions. K-NN, Pearson’s cross-correlation (CC) and ensemble-bagging methods were adopted. The results were compared after eliminating less active channels in combined method. Channel-wise CC was used to identify docile channels in training matrix and dismissed from the test matrices. Figures 6.10, 6.11 (on pages 135, 136), depict the results for gesture recognition. Figure 6.11 on page 136 gives the mean difference between two instances of gesture match or mismatch conditions. Combined CC and KNN exhibit greater ∆r suggesting less room for misinterpretation of gestures. This is beneficial when there are many gestures and postures to be recognized for advanced prosthesis control. In average combined CC and KNN gives 0.86% and 0.69% difference whereas KNN, CC and Bagging methods give 0.59%, 0.39% and 0.45% respectively. There is a 21% improvement of using combined classification scheme. The highest difference is observed from the KNN method. In conclusion, KNN classification method demonstrated 14.4% improved gesture recognition rate compared to others.

6.6.1 Degradation with Time

During the data collection, each subject executed the gestures from thumb to small finger flexion/extension, G1 - G5. The results shown in Figure 6.12, correlation and classification characteristics deteriorated by ∆0.038 and ∆0.056 for combined and standard respectively, by the time G5 being executed.

The reason for this phenomenon can be explained as the US coupling medium being squeezed out due to the longer wearing period. The body heat could affect the viscosity
Figure 6.12: Recognition degradation with time from G1 to G5. The phenomenon was observed for all 10 subjects, mean is given above.

Of US coupling gel hence changing the coupling characteristics and uniformity. A notable ambiguity was the coupling medium drying out. The ambient temperature during the data collection was 31. However contrary to sEMG method, sweat or moisture on the skin could positively affect the skin-transducer interface as water has similar acoustic impedance to soft-tissues (Wells, 1998).
Chapter 6. Proportional Control

6.7 Summary

This chapter presented experimental results by employing the WURMADS hardware to evaluate the feasibility of proportional control of prosthesis hands. The study was based on amputee subjects who executed supervised gestures. The results suggested that 3D ultrasound imagery with window based tracking algorithm can successfully predict the contraction levels of a digit. Although it was difficult to obtain visual feedback from amputees of their gesture execution, limb mirroring was proved to be efficient with $6.60 \pm 2.62\%$ of synchronization error. A model based approach is utilized to predict 10 contraction levels with $90.27 \pm 1.79\%$ accuracy. The results are highly encouraging and the method can be easily implemented in portable SMG systems to facilitate proportional control. In the second part of the chapter, efficient template based gesture recognition method was introduced. Combining cross correlation and kNN classifier proved to be efficient in recognizing simple digit flexion/extension gestures. The idle channel elimination method reduced the classes in the classifier and improved the overall recognition rates. It also provided greater difference between matched and unmatched gestures that helps to distinguish gestures efficiently. However, degradation of the signal with time is a problem that need further attention. An improved wearable cuff to hold the transducers steady can help the degradation of the signals with time.
Chapter 7

Submerged Gesture Recognition with Alternative Coupling Medium

7.1 Introduction

This chapter presents an exclusive study on gesture recognition ability of WURMADS in underwater environment with alternative oil based long lasting coupling medium. At the time of writing, there is no reliable forearm muscle activity detection system to control dexterous prosthesis in such conditions. In the second part of the chapter, WURMADS is used to investigate morphological changes during isotonic contractions with different applied tensions. The results will be help to understand the impact of tension on forearm muscles morphologically during dynamic contractions. The experiment employed 7 healthy subjects.

In this section we mainly focussed on answering two questions.

- An alternative coupling medium that suited for underwater usage
- Ability to recognize gestures in underwater using WURMADS.

Presently, there are no dexterous prostheses that controlled by US. WURMADS is the first of its kind to facilitate this with several benefits that stated throughout the thesis. In practical sense, US based prostheses control requires a better coupling medium to transfer energy into the forearm. Unlike sEMG in which the electrodes can be dry, US
requires a medium, ideally which has the same acoustic impedance as the skin/soft-tissues. Unfortunately coupling mediums with such properties are of liquid in nature. This makes it difficult to apply standard US gel in a tight space inside a prosthesis. We also observed that in an environment where the ambient temperature is 30°C or more, standard US gel becomes viscous and dries out quickly. This limits the wearing time and demands an alternative approach to solve this problem. In this study we investigated the feasibility of using non-drying oil alternative and compared the results with conventional US gels in both water submerged and normal conditions.

Contrary to sEMG electrode attachment, US requires a coupling medium to provide smoother interface to transfer acoustic energy into the skin. Without such medium, due to the higher acoustic impedance at boundaries, most of the energy will not be transferred through the skin providing no valuable information. Considering the practicality in dexterous prosthesis applications, having to apply water based coupling medium can be problematic. In this section, an alternative and long lasting coupling medium will be tested against water based standard ultrasound gel.

7.2 Coupling Medium Test Set-up

The objective of this experiment is to evaluate the efficiency of three different popular coupling mediums and their characteristic degradation over an extended time period. Followings are the used coupling mediums:

- Standard US water based coupling gel (Anagel, Surbiton, Surrey, UK)
- Virgin Olive oil
- Water

For the applications of dexterous prosthetic control, ability to support lengthy wearable period is an important factor. Water based US gel has a greater tendency to be dried out after a period of time hence diminishing the performances. This section investigated the usability of above three mediums over a fixed time interval. Olive oil has similar acoustic characteristics as standard US gel with 1.32 MRayls of acoustic impedance whereas water has 1.48 MRayls. A study revealed that (Luewan et al., 2007) olive oil demonstrate similar image quality as US gel. It is also cheaper, readily available and lasts longer as it is a non-drying oil. Non-drying characteristic comes from the Iodine value of the oil, which is the marker for unsaturated fatty acids. Iodine values less than 115 are generally considered non-dying oil. Olive oil has Iodine value of 80-88 which
is highly unsaturated in fatty acids making it last longer when applied on human skin. Olive oil has a slow absorption rate making it ideal for longer wearing periods without having to reapply. Olive oil has a very low melting point (-6°C) which is ideal for outdoor applications during the winter months. The heat generated by skin itself is enough to keep the oil from solidifying. Water on the other hand as a coupling medium used mainly for therapeutic applications rather than diagnostic.

Figure 7.1: Experimental setup: Session was timed for 2 hours with M1, M2 and M3 coupling mediums. M1 = Water, M2 = Olive oil and M3 = standard US gel

Figure 7.1 shows the experiment set-up. Three 5MHz transducers were used to evaluate the amplitude degradation of the echo pulses. A plastic sheet was installed 2.5cm from the inner wall of the plastic container, which is the water bath. Transducers were installed on the outside wall of the container with previously stated three coupling mediums. The reflected echoes by the plastic sheet from each transducer were recorded for 2 hour period. In order to simulate the real-world conditions inside the prosthesis sockets and drying, a fan was installed to blow heated air at steady rate. However the temperature at the transducers was maintained to be constant at 30°C.
7.2.1 Coupling Medium Test Method

The measured feature in this experiment is the amplitude of the reflected echo from each transducer. The amplitude of the reflected echo from the plastic sheet is directly proportional to the energy entered the water bath. If the coupling medium is weak, or having a high acoustic impedance at the boundary, that affects the reflected echo amplitude. In order to find the true amplitude, Hilbert Transformation (6.1 on page 122) was adopted. Each transducer was pulsed 4 times a second. The pulse burst consisted of five 5MHz pulses. Following the 2 hour data collection period, each channel’s echoes were filtered and the amplitudes were extracted to an array ($A_e$).

7.2.2 Coupling Medium Test Results

![Graph showing Amplitude degradation over time for water, oil, and gel mediums.]

**Figure 7.2:** Experiment results: Normalized amplitudes for three mediums are depicted against time

The results reveal that the energy transfer through the coupling mediums has distinct properties. At the beginning, all three mediums transferred equal amounts of energy...
to the water tank. Amplitude of the echoes through olive oil medium demonstrated no attenuation over the period of 2 hours with $30^\circ$ constant airflow. **In fact the oil coupling exhibited no attenuation even after 24 hours.** Water, however was the weakest as we can expect the airflow around the cylindrical aperture can dry out the thin layer between the transducer and tank’s face. It dried out under 30 minutes. Ultrasound gel also demonstrated a good coupling characteristics under simulated conditions but it too eventually dried out approximately after 1.8 hours. It should be noted that the absorption of all three mediums are non-existent as the tank is made of plastic. However in real conditions, skin can easily absorb water, potentially drying out even faster. Increased temperature helped to recreate the conditions inside a prosthesis and airflow mimicked the accelerated drying/skin absorption.

As a conclusion, olive oil as a coupling medium retained without amplitude degradation for an extended period of time in an artificially created test environment. It is therefore recommended for prosthesis applications with sonomyography. The next experiment is based on these findings and used olive oil as the coupling medium.
7.3 Underwater Gesture Recognition Using SMG

Recognizing the gestures underwater to control prostheses has not been attempted previously. Popular sEMG technology has its own weaknesses. A study has already proven that inability to reliably detect sEMG in highly moisturised conditions (Rainoldia et al., 2004). The only solution is to use protective film to cover the electrodes to make it waterproof (Panek et al., 2007), which is impractical in prosthesis hand controllers. Exploring the feasibility to use SMG in underwater could benefit the amputees in different ways. Firstly ability to use a prosthesis in such environment will give them peace of mind to wear it even in rain without anticipating an erratic behaviour due to cross-talk etc. Secondly, wide range of job opportunities will be available to them as they can actively use the prosthesis to do tasks such as ship maintenance, swimming, riding motorbikes in rain or damped conditions etc.

Based on the results obtained in the previous section, we decided to use Olive oil as the coupling medium due to following reasons.

- Ease of application, availability, non-drying and similar acoustic characteristics similar to standard US gel
- Insolubility in water

The second point is an important foundation for this study. Previous attempts and experiences pointed out that standard US gel dissolves and changes characteristics once it mixed with water. We also observed that US gel exhibits change in viscosity with temperature. In some occasions it poorly adheres to the transducer surface. This mostly occurs in cold environments. In all cases this adversely affects acoustic energy transfer to the skin. One of the notable advantages of US is its immunity to electrical noise. It also won’t affected by moisture, although added moisture can positively affect the performances. According to the available literature there are no studies that have been done to investigate the efficiency of alternative coupling mediums with standard US gel in dexterous prosthesis control applications.

7.3.1 Experimental set-up

For this experiment several gestures have been performed both above and underwater.

- Wrist flexion
- Fist hand
Chapter 7. \textit{Submerged Gesture Recognition with Alternative Coupling Medium}

- Small and ring finger flexion
- Index finger and thumb abduction

We employed 7 healthy subjects, 3 female and 4 male individuals, \(( \leq 75Kg, \text{male}, 28-36 \text{ of age}, \text{average forearm circumference of 22cm})\) for the experiment. None of the subjects had a history of muscular disorders or discomfort during digit flexions/extensions. Subjects were sat comfortably in front of a table while resting their right arm on the table in supine orientation. Quasi-radial transducer rings were worn on both dorsal and ventral sides of the forearms of each subject. Gestures were performed in two phases. Each of them performed the stated gestures in air followed by the repetition of the same gestures submerged in water. They were asked to do 15 and 10 repetitions for each gesture.

In Figure. 7.3 1(A) shows the applied olive oil layer on the forearm (which is barely visible). C and B are the two transducer rings that are adjustable to suit subject’s forearm circumference and comfort level, although none of the subjects complained of any discomfort. 2(D) shows the forearm is immersed in a water bath, 2-3cm from the surface. The water bath was 90cm (L), 60cm (W) and 30cm(D) in size.

Subjects were trained adequately prior to the data collection. The training and data collection process is depicted in Figure. 7.4 on page 148. A computer screen was placed in front of them that graphically depicted a visual stimulus. The stimulus displayed the number of repetitions, the gesture being performed, time elapsed and remaining gestures to be performed. The subjects were asked to familiarise with the stimulus by one or two practise sessions depending on the individual. The stimulus image was a color bar that proportionally indicate 0\% to MVC. However subjects were asked to not contract muscles to the discomfort zone. As earlier stated, amputees widely execute isotonic contractions as there is no load imposed on the muscles. This can be translated in healthy subjects by only performing the contraction in isotonic phase but avoiding the isometric phase in which the contraction is ended but the muscles are further energised and strained. Each session per subject lasted 10 minutes in average and consisted of two phases. This dataset was referenced as DB3. In the first phase, training and test sets for each gesture were acquired, a few centimetres above water (dry). Once this is completed, the forearm was submerged in water and repeated the same set of gestures 10 times each. Both phases were synchronized to the stimulus. Once submerged, it waited a few seconds before the gesture execution. This allowed water to properly soak the apparatus and remove any trapped air. Data were captured by WURMADS hardware and transferred to the PC in real-time. The scanning frequency was set to 4Hz. A PC data capturing software that we previously developed in Visual Basic, collected US signals of 8 channels.
Figure 7.3: Experimental setup and gestures performed. B and C depict quasi-radial 5 transducer (ventral) and 3 transducer (dorsal) rings respectively. Image 2 shows the submerged position of the forearm in a water bath. G0 - G4 are the gestures that performed in dry and wet conditions and saved as 1000x8 matrix in text format. Each matrix was associated with stimulus status information, such as indicated contraction level as a percentage ($F_C$) and time.

Due to low frame capturing speed of WURMADS (4-6Hz) it required the subjects to maintain the posture at MVC for a few seconds to gather as many frames as possible. This problem is only prevalent if data is transferred to a computer in real-time, due to communications latencies. As depicted in Figure. 7.5 on page 148, frame indices at peaks and troughs were used to segment areas of resting posture ($S_r$) and gestures ($S_g$). This segmentation is later used for data analysis.
Chapter 7. Submerged Gesture Recognition with Alternative Coupling Medium

Figure 7.4: Dataset structure and capturing data flow diagram

Figure 7.5: $F_C$, stimulus vector and segmentation
**7.3.2 Recognition: Offline Analysis**

Gesture recognition was implemented by using Pearson Cross-correlation algorithm. 1000x8 matrices ($M_T$), which are templates derived from training sets were obtained by averaging the 8-channel echo matrices at $S_g$ for all gestures, where $n$ is the number of gestures (5). From 15 repetitions that executed, first 5 were considered as the training set (Figure, 7.4). Those templates were cross-correlated with each matrix in test set.

$$M_T(x) = \frac{\sum S_g(x)}{n_s} \quad (7.1)$$

where $n_s$ is the number of frames in the segment and $x$ is the gesture identifier, that spans from 0 to 5. The initial position is 0.

For gestures 1-4, the templates were obtained by adopting an algorithm in which the pseudo code is given below.

**Data:** DB4

**Result:** Training templates for cross-correlation initialization;

```plaintext
for i = 1 to i = 4 do
    M_T(i) = \frac{\sum S_i(i)}{n_s}
end
M_R = \frac{\sum_{j=5}^{j=1} S_r(j)}{n_s}
M_T(0) = M_R
```

**Algorithm 2:** Training template generation

where $j$ is the number of repetitions in $S_r$ segments set. The resting position is common for all gesture execution types. However $i$ is the block identifier for gesture segments. At the end $M_T$ contains 5 templates derived from training set that is used in gesture recognition stage.

$$r(x, y) = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n \sum x_i^2 - (\sum x_i)^2} \sqrt{n \sum y_i^2 - (\sum y_i)^2}} \quad (7.2)$$

where $x = M_T(0-4)$, $y = F(v)$, $r$ is the correlation coefficient and $i = \text{number of observations}$. $F$ is the frames in the entire dataset and the frame index is given by $v$. Gesture recognition process based on correlation can be further elaborated as follows.

As depicted in Figure, 7.6, T0 - T4 templates were cross correlated with each data frames (Matrices) in the dataset (DB3). The results were stored in arrays $r(0 - 4)$, where $-1 \leq r \leq +1$. Higher the value of $r$, greater similarity is observed between templates.
and test data (F). Once the correlation is completed for all 5 gestures, highest correlation is extracted and labelled as the matched gesture along with frame index vector \((G_r)\). At a previous stage, \(F_C\) vector is used to extract the gesture and resting segments (Figure. 7.3 on page 147) and corresponding indices. It should be noted that accelerometer data was not analysed due to practical difficulties to use it in underwater. However the captured segments are centred in troughs and peaks, well cleared of transitional regions of \(F_C\). Therefore the image frames captured in the segments are stable although real accelerometer data is not used. Recognition rate evaluation was carried out in two phases, one for above water, and the other for submerged condition. Test data indices and corresponding indices in output gesture array \((G_r)\) were compared to extract number of true hits of a particular gesture.

True gesture indices for dry (above water) gestures is \(I_{d(n)}\) and similarly for wet gestures (submerged) \(I_{w(n)}\), where \(n\) is the gesture identifier.

\[
A_{n(dry)} = I_{d(n)} \cap G_r
\]  

\[
A_{n(wet)} = I_{w(n)} \cap G_r
\]  

\(A_n\) contains the number of gesture matches within the known gesture segment indices\((I)\). Let \(N\) be the number of true gesture frame indices. Therefore the recognition rate \((P)\) is given by,
\[ P_n = \frac{A_n}{N} \times 100 \]  \hspace{1cm} (7.5)

where \( n \) is the gesture identifier. 7.5 is used to evaluate recognition rates for both dry and wet conditions.

### 7.3.3 Results and Discussion

The results suggest that all the subjects demonstrated a high recognition rate for each gesture executed above and under water conditions. In average, 99.2\( \pm \) 0.26\% and 95.8\( \pm \) 4.42\% recognition rates were achieved for dry and wet conditions respectively (Figure. 7.7). Subject 1 has the lowest dry and wet recognition rates. Although high recognition rates were achieved, one of the notable observations was the reduction is correlation coefficients in wet conditions (Figure. 7.8). Similarity between the matching template and the test data obtained at gesture segments \( (S_g) \), were 0.89\( \pm \) 0.0098\% and 0.805\( \pm \) 0.0213\% for dry and wet respectively. This gives the difference as percentage \( (r^2 \times 100), 14.4\% \), compared to 3.4\% detection error. It is evident that when the forearm is submerged, the morphological structure changed resulting a lower correlation. However this change has common characteristics shared by all gestures, as the gesture recognition rates were still high. This suggests that the conditional change of moving the forearm into the a water tank, has a common effect throughout the gestures and it is predictable.

**Further Observations** - A previous test carried out with standard US gel revealed that it dissolves with water soon after submerged in the water tank. Most US gel are manufactured to be water soluble, making it easier to wash away following a clinical analysis. After a few gesture repetitions, we observed that the received echo signal quality considerably degraded due to the gel dissolution. Another notable problem was the drying. Since US gel is water based, high ambient temperature results increased viscosity, therefore dripping away and drying faster. These characteristics of US gel, hinders the use of standard US gel with prosthetic applications.

It is difficult to obtain a large number of features from US channels or matrices as an image. In some gestures the differences can be very small and confined to a channel or two. However myoelectric signals, sEMG consists of several notable features such as wide frequency spectrum, time varying amplitude, root-mean square value and so forth. Although bio-electric signals are an establish mean of controlling prosthesis, it cannot be operated in highly moisture and wet conditions. This chapter successfully demonstrated the WURMADS ability to operate underwater without a significant reduction in performance. We conclude that US methods can be successfully adopted in robotic prosthesis to operate reliably in extreme conditions. The evidence also suggests that Olive oil as
an alternative coupling medium is suitable for prolonged periods of operation without being affected by temperature and moisture.
Figure 7.8: Average gesture recognition rate per subject and correlation coefficient difference between dry and wet conditions

7.4 An Investigation of Isotonic Force and Morphological Changes

In this section muscle morphological changes at different digit torque levels with isotonic contractions are characterized. In forearm amputation, trans-radial is the preferred method over dis-articulation which is normally done 2cm from the joint to allow the prosthetic fit. In sEMG applications, this is also useful to obtained at least low levels of myoelectric potentials for powered prostheses control. In a previous study we examined 10 trans-radial amputees and their ability to activate forearm muscles. In 90% of the cases, they managed to activate the muscles that are relevant to five digit flexions. However, the observed contractions are isotonic with minimum reported resistance and
pain/fatigue developed along with the contraction. This as an unique feature, although other researchers have rarely emphasized this, specially on the studies based on EMG.

Studies on isotonic contraction are predominately confined to health related (Isokinetic) and rehabilitation exercises. In definition MVC is the maximum tension a muscle can produce and hold, but briefly. This contraction is mostly referred as Isometric Contractions in which the muscle length is kept constant. This is also called Maximum Voluntary Isometric Contraction (MVIC). MVIC is the standardize method to evaluate muscle strength in patients with neuromuscular diseases (Meldrum et al., 2007). The relationship between surface EMG and muscle force is a well studied context (Schwartz, 2012). Isometric contraction give the investigator the ability to measure it using force sensors in intact subjects.

7.4.1 Muscle Contraction Anatomical Model For Healthy Subject

Tetanic region of muscle contraction occurs when the motor unit (MU) is stimulated maximally by high frequency neuron impulses. MU activation occurs as a twitch, a narrow electrical impulse but not proportionally or sinusoidally. If the frequency and activation potential are low, the muscle is technically relaxing. However once the frequency is increased, this relaxing period decreases, producing more tension from the group of motor units. Muscle EMG frequency and force are directly related. The recording range of sEMG frequency spans from 0-400Hz Luca et al. (2010), however the useful range spans from 0 - 100, including the tetanic contraction region (THOMAS et al., 1991). In the frequency spectrum, the highest energy can be observed around 100Hz (Basmajian and Luca, 2001) and it is also a good indicator for the muscle fatigue as well. (Freund and Takala, 2001) presented a comprehensive bio-mechanical model for the forearm, palm and fingers. The model supported 61 muscle-tendon units and 8 sections.

Isotonic and isometric contractions are widely discussed in physical fitness and rehabilitation exercises. Isotonic contractions can be divided into to two groups.

- Concentric contraction - where the force generated by the muscle is always less than the maximum force the muscle can generate.

- Eccentric contraction - in this type of contractions, the muscle actively lengthens. A good example is trying to sitting down on a chair. During this action Rectus Femoris muscle (Quadriceps) eccentrically lengthens while keeping or reducing the
activation level. This gradually decreases the activation and controls the sitting down process preventing from falling on to the chair.

The objective is to measure the deviation of morphological changes in the forearm during isotonic contraction against the muscle tension, which is the most prevalent type of contraction in amputee subjects. However the tension can be negligible in most cases. In trans-radial amputees remaining muscle tendons are freely movable which is a unique feature. This is equivalent to the normal digit flexion/extension by intact individual without significantly activating/stressing the muscle at the end of the isotonic contraction phase. This mechanism can be further illustrated by the following diagram (Figure. 7.9 on page 156). We kept the applied load/tension small and below the maximum tetanic tension the muscles can generate. Surprisingly there is no study have been conducted in this context to investigate the morphological feature changes during isotonic contractions in the forearm with tension.

In surface EMG detection regime, muscles need to be contracted in isometric phase in order to generate significant myoelectric signals. In isotonic contraction without any load, myoelectric generation can be negligible, or if present, it will suffer from poor signal-to-noise (SNR).

It is also a known factor that muscle fatigue can distort the features of sEMG signals. However studies suggest that isotonic contraction reduces the tetanic force faster than isometric contractions. The author investigated these phenomenons in chapter 5. According to the available literature, muscle fatigue mostly associated with isometric contractions and is a well studied context. Unfortunately the outcomes of those researches may not be directly applicable or relevant to the robotic prosthetic hand control as the contraction is not isometric.

For dexterous prosthesis control the important parameter is the signal detection. A study (Bowen et al., 2002) revealed that dynamic gestures (isotonic) produced significantly lower sEMG peak potentials. There is no definitive way to evaluate the level of contraction produced by the subject.

During the amputation surgery, sometimes dissected tendons attached each other and placed between ulna and radius bones. It such situations, it is possible to have some resistance against the muscle contraction but it is not always the case. However the effects of this resistance has not yet fully understood morphologically in isotonic contractions. In this study we have examined the morphological changes of the muscles with different tensions. It should also be noted that contrary to sEMG, the muscle force variation can only be monitored by analysing the morphological changes of US signals as we applied lower tensions.
7.4.2 Data Collection Protocol

For the data collection from healthy subjects we used WURMADS hardware and Quasi-radial transducer array. We only utilized the 5-transducer ring, in semi quasi-radial arrangement. We employed 7 healthy subjects, 3 female and 4 male individuals, (≤75Kg,male, 28-36 of age, average forearm circumference of 22cm) for the experiment. None of the subjects had a history of muscular disorders or discomfort during digit flexions/extensions. Subjects were sat comfortably front of a table while resting their right arm on the table in supine orientation. A thread is connected to the weight is attached to the dip joint of the index finger, which is one of the strongest and controlled by flexor and extensor digitorum muscles. The weight is freely hanging through a pulley. An three axis accelerometer is also fixed to the tip of the finger, where the string is attached, to acquire angular information during finger flexion/extension. WURMADS was attached to the forearm of the subject. For this experiment only 5 ring band was utilized as the intention was to target a single muscle boundary instead of patterns from both dorsal and ventral sides. Only the index finger was flexed with a resistive force as shown in the diagram (Figure. 7.9).

![Figure 7.9: Experimental setup: A - Accelerometer. Trajectory of the finger flexion is shown in red (index finger)](image)

Each subject were asked to perform 20 flexions synchronized to the displayed stimulus (Guide). The stimulus was a graphical presentation of 0-100% (FLMIC) on a computer monitor. For each subject, 20 flexion/extensions were repeated 3 times at different applied tension levels generated with the masses of 0, 0.1, 0.2 and 0.3 kg. The horizontal distance travelled by the digit during contraction is proportional to the reduction in length of muscles in the forearm. It should be noted that the horizontal distance may
not be the true representation of the physical reduction of muscle length due to semicircular trajectory, but proportional. This is due to the mechanical leverage that follows a non-linear path. However, this will not affect the resistive force exerted on the muscle. In total, each subject performed 60 flexion/extensions during the session. WURMADS hardware produced US data frames at 5Hz and stored at a directory specified by the operator for further analysis. During the sessions three types of data were collected, US images, accelerometer and stimulus data. The range of the stimulus data was 0-100, representing the contraction level. When the digit is at extended position, which is horizontal to the surface of the table, the force was acting horizontally, pulling the digit. However, subjects were advised to keep the forearm steady and relaxed so undesired muscle activations will not corrupt the true readings.

7.4.3 Method

Although the studies based on US gesture recognition is image based, with WURMADS it is possible to extract A-mode signals from individual channel. Unlike in sEMG applications, US does not provide features such as a wide spectrum of frequencies that corresponds to fatigue. Three different weights give the following resistive forces (taking \( g \) as 9.81 \( ms^{-2} \)),

<table>
<thead>
<tr>
<th>Case</th>
<th>Force (N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.981</td>
</tr>
<tr>
<td>B</td>
<td>1.962</td>
</tr>
<tr>
<td>C</td>
<td>2.943</td>
</tr>
</tbody>
</table>

| Table 7.1: Applied resistive forces |

The subjects were also asked to execute finger flexions without connecting any weights and labelled the data as N (Neutral). This set of data is considered as the reference to evaluate the deviation of A, B and C.

For different subjects, positioning of the quasi-radial transducer band slightly varied. Therefore, for the same finger flexion, echo patterns varied for each subject. To isolate the most active channel during the flexion, Pearson Cross-correlation algorithm (Shi et al., 2010a) was used to measure the similarity between the A-mode signals obtained at maximum contraction and resting position. Each subject produced four sets of data A, B, C and N. Each set was segmented into two groups based on the accelerometer data (\( \theta_{xyz} \)). Two segments consist of US frames captured at FLMIC and resting posture (\( F_i \in \mathbb{Z} \)), against their frame indices. Once the segmentation was done, A-mode signal was averaged to reduce noise and jitter between the signals. At FLMIC and resting positions, subjects maintained the posture long enough as per the graphical stimulus to
acquire enough frames. So the averaged signal is obtained at those postures according to the indices.

\[ T_{A,B,C,N} = \frac{\sum S}{n} \]  

where \( n \) is the number of frames and \( S \) is the signal at MVC and resting postures. Likewise mean signals were extracted for A, B, C and N datasets \( T_{A,B,C,N} \). First five repetitions and the rest were taken as training and test data.

Unlike in sEMG, US A-mode signals contains a fewer features. The frequency spectrum is predominantly confined to the fundamental excitation frequency. Therefore frequency domain analysis is not applicable for this study. A FFT analysis revealed only a single energy concentration at the fundamental frequency with no harmonics. The key features of an A-Mode signal are, amplitude, shift of peaks with time, total echo energy (Root-Mean-Square) \( RMS \) of each echo profile and AUC (Area Under the Curve). In this experiment we only focussed on a single channel waveform and overall pattern deviation is considered for different loads.

7.4.4 Results and Discussion

A-mode single channel echo pattern change is depicted in Figure. 7.10. In that example, the channel was selected based on the most activity during the task. The first prominent
peak, which is a superficial muscle boundary, has clearly changed with increase in tension applied to the finger. The resting waveform (green) is taken when the finger is at extended posture, regardless of the applied tension.

Morphological changes between N-A, N-B and N-C evaluated and compared (Figure. 7.11). For example N-A denotes the difference in r at FLMIC postures of 0kg tension and 0.1kg tension applied to the finger. Ideally with no tension applied to the finger, correlation coefficients at FLMIC must be similar during each repetition. It won’t be exactly the same but can deviate by a small margin. However as the weight increases, there is a clear reduction in coefficients. This is evident from Figure. 7.12 on page 161, where it shows the individual channel and mean coefficient reduction of all channels. In the case of all channels, in which the complete images (matrices) are correlated, the change appears mostly linear for all the subjects. Change in coefficient ($\sum \Delta r/7$) is 0.2887 ± 0.067(SD), which is nearly 8% of morphological change in the muscle from the targeted channel. When the overall change is measured by taking all eight channels, and their deviation, we get 0.109±0.017, which is nearly 1.2% of morphological change.

To generalize the effect on muscle morphology with increasing tension, we obtained the mean results for all 7 subjects. Figure. 7.13 on page 161 shows the linear trend line and near-linear relationship for both single and all channels for different levels of tension. However $\Delta r$ varied with consistent margins when all the channel variations were considered. $\Delta r = (0.144 \pm 0.051$ and $0.054 \pm 0.004$) were obtained for single and multichannel marginal variance respectively.

The cross-correlation results depicted in Figure. 7.11 are given in Appendix D.

### 7.5 Summary

Findings of this study reveals that the low-level contraction with maximum of 2.9N(0.3Kg) tension could result nearly 8% of morphological changes if most active channel is focussed or else 1.2%. The results are based on 7 intact individuals. The relationship between muscle CSA and isometric contractions has been reported in previous studies. (Brors-son et al., 2008) evaluated the forearm muscle CSA, volume and thickness with finger extension using standard US imaging systems. They found that in men, muscle volume and muscle CSA were related to extension force, while for women muscle thickness was related to the extension force. A study based on isometric ramp contraction of RF (Rectus Femoris) muscle in the lower limb (Guoa et al., 2010) revealed that, change in MVC from 0 - 90% resulted a reduction in CSA of the muscle by 7.25%. (Chen et al., 2014) noted the lack of research on the areas of muscle CSA analysis in dynamic or isotonic contractions. In their study, they investigated SMG response against EMG and MMG
Figure 7.11: Results: Correlation between no-tension FLMIC and tensioned FLMIC 5-channel pattern variation data during the isometric ramp contraction of RF (Rectus Femoris) muscle. Polynomial regression of torque and CSA relationship revealed as curvilinear.

As a detailed SMG based study with both amputees and intact subjects, (Zheng et al., 2020).
Chapter 7. Submerged Gesture Recognition with Alternative Coupling Medium

2006), revealed the close correlation between muscle deformation in the residual arm and the muscle flexion. In average, percentage deformation was $7.2 \pm 3.7\%$ for healthy and $9.5\%$ (Approximately) for amputee subjects. Remarkably this value is close to our results (Chapter 5) which is $12.6\%$. However there are a few distinct differences in Zheng’s experiment to ours. In their study they employed only three amputees where as ours had 10. Two of their amputees were amputated some 20 years ago, therefore lengthy indolence may have had an effect on the muscular functions. In our experiment we only employed the subjects with < 6 years old amputation. They only performed three repetitions whereas ours consisted of 20 with a visual stimulus guide, instead of an audible guidance. However, Zheng’s method to measure the muscle deformation is quantitative (window based tracking), where as our cross-correlation based method is biased towards qualitative. Although they are largely proportional as the qualitative changes, it also proportional to the image’s morphological changes.
Above detailed researches also influenced the design of our experiments with WUR-MADS to investigate. This chapter also presented unique experiment to recognize hand gesture in submerged conditions using SMG. It used non-drying, water insoluble oil to couple the transducers to the skin underwater. We also provided evidence to support the applicability and longer usage durations of non-drying oils in SMG. The results are highly encouraging for submerged gesture recognition. In average, 99.2± 0.26% and 95.8± 4.42% recognition rates were achieved for dry and wet conditions respectively. This suggests that SMG can be used in extreme conditions where sEMG fails to operate reliably.
Chapter 8

Conclusions and Future Work

8.1 Conclusions

This thesis presented the evidence to justify the usability of sonomyography as muscle activity sensing method to control dexterous prosthesis. The datasets used in the thesis are acquired by a new wearable US forearm muscle activity sensing hardware (WUR-MADS). We employed amputees to test the hardware and methods to investigate the hypotheses we made initially. Amputee population in the world is ever increasing. Vascular disease 54% including diabetes and peripheral arterial disease, trauma 45%, and cancer less than 2% are considered main causes for the limb losses (Web). In powered prosthesis, the dexterous functionality and operation is a prime importance. Although mechanically it is feasible to manufacture prosthesis with high degree of freedom, the notable gray area is the controller. With technologies like 3D printing became widespread and cheap, manufacturing of complex mechanical devices such as dexterous prosthesis became technically less challenging. A recently published article (Zaman) evident this.

The current prominently used technology to control powered prosthesis, which is sEMG, has stagnated in terms of technology. It cannot move further without an alternative approaches to solve the inherent problems. The most prominent is the inability visualize deep muscle activities, cross-talk and fatigue inducement. However many researchers are working on improving the recognition methods without a significant breakthrough over past decades or so. Therefore it is an vital requirement to find alternative methods to detect forearm muscle activities. This study expanded the boundary beyond sEMG and investigated the SMG approach. To facilitate this, a novel Wearable Ultrasound Radial Muscle Activity Detection System (WURMADS) with unique transducer arrangement was introduced. This covers both dorsal and ventral sides of the forearm.
8.2 Thesis Contributions and Publications

Chapter 2 covered a comprehensive survey on methodologies and hardware. We also reviewed the other available technologies that used in muscle activity detection such as Near Infrared, MMG and EMG. An NIR experiment was repeated to compare the outcome. The results were then critically analysed against the obtained results. In another study that based on US, (Tanaka et al., 2003), the author questioned some of the remarks following the experiment repetition. In addition to SMG, the author spent many days investigating the myoelectric characteristics from human forearm using Trigno\textsuperscript{TM} Wireless Systems and Smart Sensors by Delsys Inc (Natwick, USA). The weaknesses and advantages were thoroughly investigated. A graphical model is presented in Figure 2.5 on page 26, which is based on the observations, hypotheses and literature. Further discussion on the model is continued in Chapter 5 with experimental evidence.

8.2.1 WURMADS: New Hardware Approach for Quasi-Radial SMG

Chapter 3 introduced the Quasi-Radial hardware and control electronics. Electronics systems mentioned in the thesis are fully developed by the author and holds the rights to the design. There is an exception for the sEMG detection kit that was used in chapter 5 experiment. In addition to the hardware, data logging applications described in chapter 4, visual stimulus and other drivers were also developed by the author. No third party developed applications were used in this study. For the data analysis MATLAB R2012b was used. The PCB design for the WURMADS was done by Target 3001 (Eichenzell, Germany) CAD tool and the PC board manufacturing took place in the UK at Newbury Electronics (Newbury, UK).

The transducers used in the system are custom made to the specification provided by the author. Internal construction and technical specifications are presented. A detailed description of the electronic circuits and methods are presented with reference to existing hardware methods in the literature. To keep the cost and development time to the minimum, DSP based architecture was implemented. Although it may be advantageous to use FPGA based systems to minimize possible latencies by adopting multi-threading.
However this is considered as a future improvements since the preliminary objective of the study was to prove the concept. The main contributions of chapter 3 are the new hardware WURMADS and Quasi-radial transducer array concept. These two contributions guide the SMG technology towards wearable, portable, practical and more resilient concept to detect forearm muscle activities. This gap was recently cited by (Castellini et al., 2014).

Chapter 4 describes the theoretical, wave characteristic overview and test results to evaluate the spatial resolution against estimated and actual values. Experiments were carried out with custom made water-phantom. We specifically focussed on A-mode characteristics rather than 2D image formation. WURMADS is inherently limited to make series of A-mode signals and combine them to form an image matrix. Therefore beam focusing and steering evaluation are inapplicable here. Obtained results suggest that the distance measured by a single barrier gives 0.64±0.35mm error. Spacing test to measure thickness between two layers gave 0.85±0.24mm of axial error. The intended spacial resolution of the system is 1.4mm. The results are comparable with standard US systems but it may not be suitable to place WURMADS in the medical US context. Contribution: Performance analysis is presented for the new WURMADS SMG hardware concept. The results were obtained theoretically and experimentally using a water-phantom. The results were comparable with standard medical US systems.

8.2.2 Fatigue-Less Maximum Isotonic Contraction (FLMIC)

Chapter 5 presented the primary methodology that used in recognizing the gestures. Anatomical overview of the forearm is provided. This overview explains the utilization of three layers of flexor/extensor muscles in the forearm to control digits, wrist and palm. Based on the anatomical structure one can critically analyse that relying on sEMG to monitor deeper muscle activations can be troublesome and error prone. Necessity of an alternative approach is argued. While investigating the mechanism of muscle fatigue, hypotheses and argument were constructed to interrogate the term ”Fatigue-less Maximum Isotonic Contraction” (FLMIC) scientifically which is a new term introduced in the thesis. In a latter part, experimental evidence is presented to justify the three main hypotheses made. The results are strongly agree with hypotheses and justify the contraction model presented in chapter 2 (Figure. 2.5 on page 26). Furthermore, experiment design, amputee subject characteristics and dataset structure are presented.

In the second part of the chapter cross-correlation method has been introduced and analysed the amputee dataset. Results revealed a good gesture recognition rate of 97.9 ±3.75% in average for all 10 amputee subjects. Which is comparable with the recent five
digit flexion study conducted by (Sikdar et al., 2014) using wearable US system (medical US system with adopted cradle). Contribution: A new term FLMIC is introduced with experimental evidence to justify. Based on the cross-correlation method, 8 hand gestures performed by amputee subjects were successfully interpreted by WURMADS.

8.2.3 Proportional Control of Prosthesis

Chapter 6 investigated the proportional controllability of prosthesis using SMG. This subject is widely analysed in the review paper, (Fougner et al., 2012), in which it stated that there is no current prosthesis device that facilitate proportional control but threshold based on/off strategy. Our preliminary experiments showed that it is feasible to obtain proportional signals during high-level contraction. However in the SMG domain, it can be much simpler and direct to measure the degree of morphological changes as demonstrated in a recent paper by Siddhartha in which he measured the different levels of flexion based on US images (Sikdar et al., 2014). The notable advantage is, its ability to see deeper muscles and facilitate proportional individual digit control. Based on the offline data analysis of the 10 amputee subjects we found that a model based approach can predict the contractile levels with 90.27% accuracy. The results are also comparable with Siddhartha’s study.

Contribution: WURMADS ability to predict the degree of muscle flexion investigated with amputee subjects. Results are comparable with other SMG based studies that based on healthy subjects and medical ultrasound imaging devices.

8.2.4 Submerged Operation Analysis (First of its kind with SMG) and Force-Deformation Relationship in Isotonic Contractions

Chapter 7 primarily investigated the ability to use WURMADS/SMG in underwater with insoluble coupling medium. In the first part of the investigation, olive oil was used as the coupling medium since standard US gel is highly water dissoluble. Secondly, olive oil is a non-drying oil which lasts longer than standard US gel or water. We proved these characteristics in section 7.2. For olive oil, no signal attenuation was observed during the 2 hour test window, whereas other mediums deteriorated under simulated test conditions. This finding paved the way to experiment the gesture recognition accuracy in submerged conditions in water. Based on the available literature there is no proven method to control prosthesis in submerged or highly moisture laden conditions. A study has already proven that inability to reliably detect sEMG in highly moisturised conditions (Rainoldia et al., 2004). The only solution is to use protective film to cover the electrodes to make it waterproof (Panek et al., 2007), which is impractical in prosthesis.
hand controllers. Our study using SMG with olive oil as a coupling medium revealed the encouraging results. In average 99.2±0.26% and 95.8±4.42% recognition rates were achieved for dry and wet conditions respectively.

In the second part of the chapter, relationship between isotonic force and degree of muscle deformation is investigated. In this experiment tension applied to a finger was varied and the morphological changes were investigated on 7 healthy subjects. Lack of studies to investigate dynamic finger flexion and applied tension motivated this experiment with the new hardware. Two results were obtained based on single and all channels. A channel was isolated based on the most prominently activity. This is similar to focusing on the region of interest (ROI) of most activities. In single A-mode channel evaluation revealed 8% of overall morphological change and 1.2% if all the channels were taken into account.

Contribution: A non-drying oil as coupling medium for SMG is evaluated. With SMG based on 7 healthy subjects, ability to recognize gestures in water revealed for the first time with high recognition rates. Secondly the relationship between isotonic finger tension and morphological changes revealed during FLMIC.

8.2.5 Publications

Nalinda Hettiarachchi, Zhaojie Ju and Honghai Liu. "A New Wearable Ultrasound Muscle Activity Sensing System for Dexterous Prosthetic Control", IEEE INTERNATIONAL CONFERENCE ON SYSTEMS, MAN AND CYBERNETICS, 2015 Hong Kong [Published]


Patent: A patent application has been filed in China for the WURMADS hardware.

8.3 Future Work

The contributions made in this thesis can improve further. This is likely to take place in three phases as given below.
Further miniaturizing the hardware and real-time processing facilities:

With the continuous advancements in technology, such as small form-factor semiconductor devices, it is feasible to further miniaturize the electronics. In order to integrate the control electronics into the prosthesis hand itself, a flexible-Printed Circuit Board (PCB) assembly approach could help to utilize the tight spaces efficiently. Our preliminary analysis revealed that WURMADS circuitry can be easily constructed on flexible PCB that could be inserted into a curvy and confined spaces found in prosthesis sockets. Contrary to sEMG processing, a single US sample window may contain a large number of data. This demands a higher processing capacity, in terms of speed and memory (RAM). Memory restriction onboard resulted WURMADS to program only a few gestures in on-line operations mode (Hettiarachchi).

In the long run, the author considers FPGA technology should be adopted in WURMADS to make the system more efficient. However there is a trade off between development time and cost compared to DSP counterpart. A notable problem we faced regarding the WURMADS is processing speed. Close to 100MHz instruction execution speed was not satisfactory in communications mode, in which the data is required to transfer to a computer. A prominent disadvantage of DSP is its inability to multi-thread tasks in parallel whereas the FPGA technology excels in it. Apart from FPGA, System on Chip (SoC) is another emerging technology in customizable high speed designs that also be considered. All technologies have their pros and cons, but US systems demand high speed real-time processing capabilities than sEMG. It is also feasible to emulate DSP on a FPGA chip if required. Parallel processing is an attractive feature to load all ADC channel data simultaneously and obtain the outputs following the required processing simultaneously. This is impossible to do in DSP environment as the instructions are executed sequentially.

Transducer arrays:

This thesis introduced a novel transducer architecture, Quasi-radial. Presently due to technical constraints, such approach is only be fulfilled by using single element (standalone) transducer arrays. However to acquire better resolution, it is vital to use higher number of transducer elements. This requires the transducers to be even smaller (<10mm diameter) and form an arc as described in Chapter 3. Presently no medical range transducer manufacturers produce such arrays. A recently published paper (Wang et al., 2015) describes a flexible ferroelectric lead zirconate titanate (PZT) transducer that suitable for heart imaging at 2MHz. If this technology further improved, construction of wearable prosthesis limbs can be further simplified to accommodate SMG sensors with ease (WURMADS for
example). In a similar effort (AlMohimeed et al., 2013) also introduced a PVDF piezoelectric polymer film based very low profile transducer. However its size must be reduced to achieve a higher spatial resolution in wearable applications. Also note that (Hettiarachchi) is the only demonstration of SMG in real-time on a fully wearable system.

Quasi-radial sonomyography is based on solid wearable transducer rings with 8 transducers. Higher the number of transducers will provide improved spatial and temporal resolution, therefore more features can be extracted. Integrating high number of smaller diameter transducers in an annular, requires a new approach to assemble and control. Presently there is no annular (or radial) shaped transducer assemblies commercially available. However it is possible to manufacture individual transducers with <8mm diameters. High-speed DSP based system with reserved RAM, instead of a FPGA, could reduce the costs as well as reconfigurability. In hardware design, we proved this by using a DSP instead of a FPGA with an additional FIFO buffering stage to handle data bottlenecks.

Sonomyography can also be used in studies on human hand motion analysis (Ju and Liu, 2014). In multi-sensory integration, sonomyography can play a vital role as it doesn’t interfere or affected by myoelectric signals. Functional Electrical Stimulation (FES) is used to stimulate peripheral nerves to activate paralysed muscles artificially to renovate the functionality in disabled. Presently as a real-time feedback method for closed-loop operation, sEMG is widely used (Yeoma, 2010)(Naomi and WK., 1997). However Residual Stimulation Artefacts (RSA) can readily corrupt the sEMG signals. This problem can be addressed effectively by using sonomyographic approach as it doesn’t affected by stimulation currents. This approach can potentially provide good tracking performances in FES.

• Real-time gesture recognition algorithms:

The distinct difference between sEMG and SMG is the fixed nature of signals from US transducers. Even at times when the arm is at rest, SMG produces patterns that only slightly different to the gesture’s. As verified in Chapter 5, muscle tension or force generated has no significant impact on the SMG signals against the resting posture. However in sEMG there is a direct relationship of force and sEMG signal features. Adopting efficient on-board gesture recognition algorithm could be highly beneficial in low density SMG systems like WURMADS. However this requires capable electronic architecture with adequate RAM and speed.

Since WURMADS is based on low density transducer arrays (unlike 100s of element arrays in medical systems), processing latencies can be minimised if multi-core high
speed DSP is utilized. However FPGA with higher RAM DSP can boost the overall efficiency in real-time algorithm execution. Such architectures involving both FPGA and DSP are recently proposed by several US chip set manufacturers such as Texas Instruments and Analog Devices.

Present technologies that control prostheses extract physical quantities such as voltage, vibration or acoustic signals (MMG) that generated by the muscles. With numerous research activities in these particular areas have already proven that no significant contributions can be made any further. The author considers these techniques are well understood and technologically stagnated for years. Now the priority should be diverted to investigate methods that could visualize internal muscle activities non-invasively. Therefore it is a vital importance to examine other possible methods to satisfy ever increasing dexterous prosthesis control requirements. Although it may sound preposterous, methods like CT, MRI, X-Ray and radiography can be miniaturized with the advancements of technology in the near future. This will surely pave the way to new prospects. As a matter of fact, two decades ago portable US systems were considered beyond the technical capabilities at that time. However with rapid advancements of semiconductor technologies, the form factor exponentially reduced.

8.3.1 Quasi-Radial Arrangement in other applications

With recent advancements in semiconductor and millimetre wave RF technologies, radar range finder transceivers became widespread and popular among electronics designers. Due to highly directive nature of very low power \(\approx 1\text{mW} \) at 5-10GHz X-Band range, they are widely used in range finding and Doppler applications. Since RF energy can pass through human tissues and at the same time absorbed by the tissues, a transceiver array can be used with proposed Quasi-radial configuration to measure the attenuation.

As depicted in Figure. 8.2, multiple receiving antennae captures the transmitted very low power RF energy from the opposite side of the forearm. Receiving antennae measure the detected RF energy levels. The author hypothesize that diffracted, scattered and absorbed RF energy by soft-tissues could result a unique pattern or variation in received RF energies. However the outer casing of the prosthesis socket must be grounded in order to prevent radiation to outside. This method is worth experimenting as there is no literature to support its feasibility.

As concluding remarks, the author would like to stress that the study presented in this thesis is original and pioneering. To this date there is no similar study that has been conducted to address practical implementation problems that hindered the evolution of SMG. In this thesis we presented a novel wearable, portable hardware and furnished with
Figure 8.2: Proposed configuration for low power microwave Quasi-radial non-invasive/non-contact muscle activity detection.

Evidence to support its functionality to control dexterous prosthesis. The experiments performed with amputees subjects and the results were proven to be highly encouraging.
Appendix A

Safety statement

A.1 Safety statement

The following statement was issued by the council of the British Medical Ultrasound Society (BMUS) in 2000 and reconfirmed in 2007 regarding the safety of diagnostic US.

A.2 Statement on the Safe Use and Potential Hazards of Diagnostic Ultrasound

Ultrasound is now accepted as being of considerable diagnostic value. There is no evidence that diagnostic ultrasound has produced any harm to patients in the four decades that it has been in use. However, the acoustic output of modern equipment is generally much greater than that of the early equipment and, in view of the continuing progress in equipment design and applications, outputs may be expected to continue to be subject to change. Also, investigations into the possibility of subtle or transient effects are still at an early stage. Consequently diagnostic ultrasound can only be considered safe if used prudently. Thermal hazard exists with some diagnostic ultrasound equipment, if used imprudently. A temperature elevation of less than 1.5°C is considered to present no hazard to human or animal tissue, including a human embryo or fetus, even if maintained indefinitely. Temperature elevations in excess of this may cause harm, depending on the time for which they are maintained. A temperature elevation of 4°C, maintained for 5 minutes or more, is considered to be potentially hazardous to a fetus or embryo. Some diagnostic ultrasound equipment, operating in spectral pulsed Doppler mode, can produce temperature rises in excess of 4°C in bone, with an associated risk of high temperatures being produced in adjacent soft tissues by conduction. With some machines
Appendix A. Safety statement

colour Doppler imaging modes may also produce high temperature rises, particularly if a deep focus or a narrow colour box is selected. In other modes, temperature elevations in excess of 1°C are possible, but are unlikely to reach 1.5°C with equipment currently in clinical use, except where significant self-heating of the transducer occurs. Non-thermal damage has been demonstrated in animal tissues containing gas pockets, such as lung and intestine, using diagnostic levels of ultrasound (mechanical index values of 0.3 or more). In view of this, it is recommended that care should be taken to avoid unnecessary exposure of neonatal lung, and to maintain MI as low as possible when this is not possible. In other tissues there is no evidence that diagnostic ultrasound produces non-thermal damage, in the absence of gas-filled contrast agents. However, in view of the difficulty of demonstrating small, localised, regions of damage in vivo, the possibility of this cannot be excluded. The Mechanical Index, if displayed, acts as a guide to the operator. The use of contrast agents in the form of stabilised gas bubbles increases the probability of cavitation. Single beam modes (A-mode, M-mode and spectral pulsed Doppler) have a greater potential for non-thermal hazard than scanned modes (B-mode, Colour Doppler), although the use of a narrow write-zoom box increases this potential for scanning modes.
Appendix B

WURMADS Hardware Schematics
Figure B.1: Secondary Microcontroller and ADC oscillator module
Figure B.2: Digital Signal Processor (DSP)
Figure B.3: High Voltage (HV) power supply module for transducer driver
Figure B.4: System power supply units
Figure B.5: VGA, ADC and DAC unit
Figure B.6: Communications and FIFO
Figure B.7: Transmit beam-former and logic interface
Figure B.8: HV Transducer drivers and TX/RX switches
Appendix C

Gesture recognition data:
Chapter 5
Figure C.1: Chapter 5: Gesture recognition results from Cross-correlation method
Figure C.2: Chapter 5: Gesture recognition results from AUC method
### Appendix C. WURMADS Hardware Schematics

#### Figure C.3: Chapter 5: Final results comparison for both CC and AUC methods

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#### Table C.3: Shaded cells show the failed recognition instances
Appendix D

Digit tension experimental results: Chapter 6
### Figure D.1: Isotonic finger flexion with three different weights: Results

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<td>0.5628</td>
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<td>0.7777</td>
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<td><strong>0.0462</strong></td>
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<td><strong>0.048</strong></td>
<td><strong>0.1161</strong></td>
</tr>
<tr>
<td></td>
<td>Ch1</td>
<td>Ch2</td>
<td>Ch3</td>
<td>Ch4</td>
<td>Ch5</td>
</tr>
<tr>
<td>N-A</td>
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<td>0.9312</td>
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<td>0.9573</td>
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<td>0.8954</td>
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<td><strong>0.0493</strong></td>
<td><strong>0.0701</strong></td>
</tr>
<tr>
<td></td>
<td>Ch1</td>
<td>Ch2</td>
<td>Ch3</td>
<td>Ch4</td>
<td>Ch5</td>
</tr>
<tr>
<td>N-A</td>
<td>0.8966</td>
<td>0.9806</td>
<td>0.9485</td>
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<td>N-B</td>
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<td>0.8616</td>
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<td><strong>delta</strong></td>
<td><strong>0.1571</strong></td>
<td><strong>0.0614</strong></td>
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<td>Ch1</td>
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<td>Ch3</td>
<td>Ch4</td>
<td>Ch5</td>
</tr>
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<td>0.9764</td>
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<td>0.8826</td>
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<td><strong>0.0287</strong></td>
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<tr>
<td></td>
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<td>Ch2</td>
<td>Ch3</td>
<td>Ch4</td>
<td>Ch5</td>
</tr>
<tr>
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<td>0.6965</td>
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<td><strong>0.226</strong></td>
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</table>

Appendix A. Safety statement
Appendix E

KLM simulation parameter:
Chapter 4
**Appendix A. Safety statement**

**Figure E.1: Chapter 4: KLM simulation parameter**

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Transducer Aperture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center Freq. 5 MHz</td>
<td>Shape Round</td>
</tr>
<tr>
<td>Scan Start 1 MHz</td>
<td>Radius 5 mm</td>
</tr>
<tr>
<td>Scan Stop 10 MHz</td>
<td>Area 78.5 mm²</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Active Layer</th>
<th>Transceiver, Excitation, Load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material PZT</td>
<td>Transmitter Impedance 50.0 Ω</td>
</tr>
<tr>
<td>Longitudinal Velocity 4350 m/s</td>
<td>Receiver Impedance 50.0 Ω</td>
</tr>
<tr>
<td>Shear Velocity 2230 m/s</td>
<td>Excitation Type Burst</td>
</tr>
<tr>
<td>Density 7750 kg/m³</td>
<td>Burst Cycle 5.00</td>
</tr>
<tr>
<td>Impedance 33.7125 MRayl</td>
<td>Back Acoustic Load 6.0 MRayl</td>
</tr>
<tr>
<td>Attenuation 2 dB/cm/MHz</td>
<td>Back Acoustic Load 1.5 MRayl</td>
</tr>
<tr>
<td>Dielectric Constant 830 g / g₀</td>
<td>Reflection Target Distance 2.00 mm</td>
</tr>
<tr>
<td>Losstangent 0.02</td>
<td>Reflection Target Impedance 2.7 MRayl</td>
</tr>
<tr>
<td>k 0.49</td>
<td></td>
</tr>
<tr>
<td>Thickness mm 0.438 mm</td>
<td>Thickness λ 0.503 λ</td>
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**Backing Layer: Starts from Active Layer**

<table>
<thead>
<tr>
<th>No.</th>
<th>Material</th>
<th>VL: m/s</th>
<th>VS: m/s</th>
<th>Density: kg/m³</th>
<th>Impedance: MRayl</th>
<th>Attenuation: dB/cm/MHz</th>
<th>Thickness: mm</th>
<th>Thickness: λ</th>
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<tbody>
<tr>
<td>0</td>
<td>Back0</td>
<td>2000</td>
<td>1200</td>
<td>3000</td>
<td>6</td>
<td>15</td>
<td>1.5 P</td>
<td>3.75</td>
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<tr>
<td>1</td>
<td>Back1</td>
<td>2000</td>
<td>1200</td>
<td>1000</td>
<td>2</td>
<td>6</td>
<td>4</td>
<td>10</td>
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**Matching Layer: Starts from Active Layer**

<table>
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<th>Material</th>
<th>VL: m/s</th>
<th>VS: m/s</th>
<th>Density: kg/m³</th>
<th>Impedance: MRayl</th>
<th>Attenuation: dB/cm/MHz</th>
<th>Thickness: λ</th>
<th>Thickness: mm</th>
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</thead>
<tbody>
<tr>
<td>0</td>
<td>Epoxy</td>
<td>2500</td>
<td>1984</td>
<td>3000</td>
<td>7.5</td>
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<td>0.125</td>
<td>0.25</td>
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<tr>
<td>1</td>
<td>Epoxy</td>
<td>2000</td>
<td>1984</td>
<td>1500</td>
<td>3</td>
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<td>0.1</td>
<td>0.25</td>
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</table>

**Proximal Component**

<table>
<thead>
<tr>
<th>No.</th>
<th>Component</th>
<th>Name</th>
<th>Length</th>
<th>Z</th>
<th>Attenuation 0.1dB/MHz/cm</th>
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</thead>
<tbody>
<tr>
<td>0</td>
<td>ShuntResistor 50.0Ω</td>
<td>R59</td>
<td>5 m</td>
<td>50Ω</td>
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</tbody>
</table>
Appendix F

Water bath test phantom
Figure F.1: Chapter 4: Water tank phantom used to evaluate spatial resolution of the transducer and electronics. A - Acoustic absorption foam, B - Water bath, C - Transducer
Appendix G

Ethical Approval

University ethics committee approved the use of WURMADS hardware on human subjects and experimental procedures. The committee have also interrogated the electrical specification of the hardware to evaluate its safety on human subjects as it was built by the author. The hardware complies with the medical safety regulations. The chapters are based on the following experiments/dataset. (Table G.1).

<table>
<thead>
<tr>
<th>Experiment/Dataset</th>
<th>Subjects (N)</th>
<th>Ability</th>
<th>Analysed in Chapter</th>
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<tbody>
<tr>
<td>1/DB1</td>
<td>10</td>
<td>Disable</td>
<td>5, 7</td>
</tr>
<tr>
<td>2/DB2</td>
<td>7</td>
<td>Able</td>
<td>6</td>
</tr>
<tr>
<td>3/DB3</td>
<td>7</td>
<td>Able</td>
<td>6</td>
</tr>
<tr>
<td>4/DB4</td>
<td>4</td>
<td>Able</td>
<td>5</td>
</tr>
</tbody>
</table>

Table G.1: Experiments and analysed chapters
Appendix H

Figures and Diagrams Copyright

The diagrams and figures in the thesis are own creations of the author and holds the right for those images. However there are a few exceptions where the author has stated the image origination and he bears no rights.

Figure 1.1: First two images. Publicly available at http://witscience.org/ and many other online resources

Figure 1.3: Two images are originated from http://www3.gehealthcare.com/ and (Castellini and Gonzalez, 2013).

Figure 2.2: (Tanaka et al., 2003)

Figure 2.4: (Delaney et al., 2010)

Figure 5.1: http://humananatomybody.info/

Figure 3.11: Datasheet. http://www.analog.com/media/en/technical-documentation/data-sheets/AD604.pdf

Figure 5.1: Web resource http://humananatomybody.info/.
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