Investigation of Surface Defects for Extruded Aluminium Profiles using Pattern Recognition Techniques

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Abstract

This research investigates detection and classification of surface defects in extruded aluminium profiles in order to replace the traditional eye inspection which is still the method widely used today. Through an extensive literature review it is evident that extruded aluminium surface is not investigated properly, while similar industrial products such as copper strips or rolled steel have attracted more interest. An experimental machine vision system is used to capture images from surfaces of extruded aluminium profiles. Extensive feature selection is investigated and appropriate statistical features from a novel technique based on Gradient-Only Co-occurrence Matrices are used to detect and classify defects. The methodology created in this research, makes use of the Sobel edge detector to obtain the gradient magnitude of the image and is followed by the extraction of statistical texture measures from the gradient, after a transformation of the gradient values. Comparisons are made between the statistical features extracted from the original image (Gray-Level Co-occurrence Matrix) and those extracted from the gradient magnitude using a novel approach (Gradient-Only Co-occurrence Matrix). The features extracted from the image processing are classified by feed-forward artificial neural networks. Experiments were conducted for a three class and a four class case study, with the first consisting of Good Surface, Blisters and Scratches, and the second introducing Die Lines to the classes of the first case study. The artificial neural network training is tested using different combinations of statistical features with different topologies. Features are compared individually and grouped, showing better classification accuracy for the novel technique (98.9%) compared to research standard methodology of gray-level co-occurrence matrices (55.9%).
Contents

Abstract ii
Declaration vii
Acknowledgements xiii
Dedication xiv

1 Introduction 1
1.1 Aluminium 1
1.2 Motivation and research objectives 1
1.3 Thesis layout 2

2 Aluminium Extrusion 5
2.1 Aluminium Alloys 5
2.2 Extrusion 8
2.3 Defects 9
2.4 Surface Defects 10
2.4.1 Tearing 11
2.4.2 Pick-up 11
2.4.3 Die-Lines 12
2.4.4 Blistering 14
2.4.5 Weld Lines 15
2.4.6 Colour Streaks 15
2.5 Surface Quality and Extrusion Parameters ........................................... 16
2.6 Summary ................................................................................................. 17

3 Automated Visual Quality Inspection ......................................................... 18

3.1 Machine Vision ......................................................................................... 18

3.1.1 Digital Camera Types ........................................................................ 18
3.1.2 Images ................................................................................................ 19
3.1.3 Obtaining Information ........................................................................ 19

3.2 Literature review of pattern recognition techniques ............................... 20

3.2.1 Classification of metallic surfaces ......................................................... 21
3.2.2 Classification of other surfaces ........................................................... 24
3.2.3 Statistical texture approaches .............................................................. 25
3.2.4 Gray level co-occurrence matrix features .......................................... 27
3.2.5 Gray level gradient co-occurrence matrix features ............................ 29
3.2.6 Illumination ......................................................................................... 30

3.3 Summary .................................................................................................. 31

4 Image processing and feature extraction .................................................... 32

4.1 Machine Vision Introduction ................................................................ 32

4.1.1 Image enhancement ........................................................................... 32
4.1.2 Gray-level value transformations ....................................................... 33
4.1.3 Image smoothing ............................................................................... 33
4.1.4 Image segmentation ......................................................................... 35
4.1.5 Edge extraction .................................................................................. 36
4.1.6 Dilation and Erosion ........................................................................ 39
4.1.7 Fitting of geometric primitives ........................................................... 41

4.2 Image acquisition .................................................................................... 43

4.2.1 Extruded aluminium profile sample set and hardware equipment .... 43
4.3 Image processing .................................................................................... 44
4.3.1 Image gradient ........................................... 44
4.3.2 Investigation of aluminium surface features .......... 46
4.4 Feature extraction ........................................... 56
  4.4.1 Co-occurrence matrix features ......................... 56
  4.4.2 GLCM results discussion ............................... 62
  4.4.3 Gray level gradient co-occurrence matrices .......... 62
4.5 Novel feature extraction ................................... 64
  4.5.1 Gradient Only Co-occurrence Matrices ................. 64
  4.5.2 GOCM results discussion .............................. 67
  4.5.3 Proposed novel GOCM methodology .................... 71
4.6 Classification methodology ................................ 72
  4.6.1 Scaled Conjugate Gradient Algorithm ................. 73
4.7 Summary ...................................................... 76

5 Surface defect classification of extruded aluminium profiles 77
  5.1 Case study: A three class problem ......................... 77
  5.2 Case study: A four class problem ......................... 82
  5.3 Summary .................................................. 87

6 Contribution and Conclusion ................................. 89
  6.1 Summary of the research .................................. 89
  6.2 Resolution of research aims and objectives ............... 89
  6.3 Contributions .............................................. 92
  6.4 Discussion ................................................ 93
  6.5 Future Directions ......................................... 94

Bibliography.......................................................... 96

A Interview............................................................. 106
B Halcon code 108

C Matlab code 113

D Sample set 119

E Ethical Review 122
Declaration

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.

The word count for this thesis is 16714.

(Apostolos Chondronasios)
List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1</td>
<td>Gray value measures of images in Fig 4.17</td>
<td>48</td>
</tr>
<tr>
<td>4.2</td>
<td>Gray value measures of images in Fig 4.18</td>
<td>50</td>
</tr>
<tr>
<td>4.3</td>
<td>Gray value measures of images in Fig 4.19</td>
<td>52</td>
</tr>
<tr>
<td>4.4</td>
<td>Gray value measures of images in Fig 4.20</td>
<td>52</td>
</tr>
<tr>
<td>4.5</td>
<td>Gray value measures of images in Fig 4.21</td>
<td>55</td>
</tr>
<tr>
<td>4.6</td>
<td>Co-occurrence matrix features for images of Figure 4.17</td>
<td>59</td>
</tr>
<tr>
<td>4.7</td>
<td>Co-occurrence matrix features for images of Figure 4.18</td>
<td>60</td>
</tr>
<tr>
<td>4.8</td>
<td>Co-occurrence matrix features for images of Figure 4.19</td>
<td>60</td>
</tr>
<tr>
<td>4.9</td>
<td>Co-occurrence matrix features for images of Figure 4.20</td>
<td>61</td>
</tr>
<tr>
<td>4.10</td>
<td>Co-occurrence matrix features for images of Figure 4.21</td>
<td>61</td>
</tr>
<tr>
<td>4.11</td>
<td>The difference in co-occurrence matrix calculation with Sobel and integer transformed Sobel</td>
<td>65</td>
</tr>
<tr>
<td></td>
<td>taken from a part of the same image of a blister defect.</td>
<td></td>
</tr>
<tr>
<td>4.12</td>
<td>Paired T-tests of the data</td>
<td>67</td>
</tr>
<tr>
<td>4.13</td>
<td>Co-occurrence matrix features for image gradients (integer) of Figure 4.18</td>
<td>69</td>
</tr>
<tr>
<td>4.14</td>
<td>Co-occurrence matrix features for image gradients (integer) of Figure 4.19</td>
<td>69</td>
</tr>
<tr>
<td>4.15</td>
<td>Co-occurrence matrix features for image gradients (integer) of Figure 4.20</td>
<td>70</td>
</tr>
<tr>
<td>4.16</td>
<td>Co-occurrence matrix features for image gradients (integer) of Figure 4.21</td>
<td>70</td>
</tr>
<tr>
<td>5.1</td>
<td>Artificial Neural Network topology table with MSE and Accuracy values</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>over an average of 100 tested ANNs for each feature.</td>
<td></td>
</tr>
</tbody>
</table>
5.2 Artificial Neural Network topology table with MSE and Accuracy values over an average of 100 tested ANNs for each feature group. (Legend: $C=$ Contrast, $C_{90}=$ Contrast90, $E=$ Energy, $E_{90}=$ Energy90, $H=$ Homogeneity, $H_{90}=$ Homogeneity90, $Cr=$ Correlation, $Cr_{90}=$ Correlation90) . . . . . . 82

5.3 Artificial Neural Network topology table with MSE and Accuracy values over an average of 100 tested ANNs for each feature. . . . . . . . . . . . 86

5.4 Artificial Neural Network topology table with MSE and Accuracy values over an average of 100 tested ANNs for each feature group. (Legend: $C=$ Contrast, $E=$ Energy, $H=$ Homogeneity, $Cr=$ Correlation) . . . . . . . . 88
List of Figures

1.1 Overview of the Thesis ................................................. 4

2.1 Some of 6000 series alloy characteristics taken from http://www.buildlog.net/documents/Extruded_Alloy_6063.pdf. ........... 5

2.2 $Al - Mg_2Si$ phase diagram [Zhang et al., 2001] .................. 6

2.3 Buehler microscope image of 6063 alloy billet cross-section at 500x magnification level ................................. 7

2.4 Direct and Indirect extrusion taken from http://www.aluminiumdesign.net/design-support/aluminium-extrusion/ .............. 8

2.5 Relationship between extrusion speed and billet temperature .................. 11

2.6 Tearing and blister defects (image taken using Mitutoyo QuickVision) ........ 11

2.7 Pick-up defect (image taken using Mitutoyo QuickVision) ................ 12

2.8 Die-lines on a profile (image taken using Basler Scout Camera) ........ 13

2.9 Blisters (image taken using Basler Scout camera) ..................... 14

2.10 Weld line (image taken using Basler Scout camera) .................. 15

2.11 Surface finish dependance ............................................. 16

3.1 Inspection sequence ..................................................... 19

4.1 Image smoothing using different techniques ................................ 34

4.2 Image segmentation using different techniques ........................ 35

4.3 Thresholds of two different smoothing techniques ..................... 36

4.4 Edge extraction of blisters ............................................. 37

4.5 Thresholds of image gradients ......................................... 37
4.6 Skeletons of the thresholded image gradients ............................................. 38
4.7 Edge extraction on anisotropic diffused and mean filtered images ......... 38
4.8 Thresholded image gradients after smoothing ........................................... 39
4.9 Skeletons of the thresholded image gradients after smoothing ................. 39
4.10 Dilations of Figure 4.6 ................................................................. 40
4.11 Dilations of Figure 4.9 ................................................................. 41
4.12 Fitting of circle (1.5px radius) on the dilations of Figure 4.10 ................. 42
4.13 Fitting of circle (1.5px radius) on the dilations of Figure 4.11 ................. 42
4.14 Two blister detection results using different techniques ......................... 42
4.15 Sample aluminium profile with background removed .............................. 43
4.17 Example images of 4 distinct classes .................................................. 47
4.18 Example images of non defective samples ............................................ 49
4.19 Example images of blister defect ...................................................... 51
4.20 Example images of scratch defect ...................................................... 53
4.21 Example images of die-line defect ...................................................... 54
4.22 Co-occurrence matrices of Figure 4.17 ............................................... 58
4.23 Co-occurrence matrices of Figure 4.17 after gradient calculation and integer transformation .............................. 66
4.24 GOCM statistical feature extraction methodology ................................. 71
4.25 Multilayer perceptron neural network architecture ................................ 72
4.26 Hyperbolic Tangent transfer function ............................................... 73
5.1 Class distribution of the sample set .................................................... 78
5.2 Box-and-whisker diagram of the feature matrix .................................. 78
5.3 Scree plot of the principal components with 95% total variance ............ 79
5.4 Bi-plot of principal component coefficients and scores for first two principal components ........................................ 79

5.5 Scatter plots of a random selection of features .................................................. 80

5.6 Class distribution of the sample set ................................................................. 82

5.7 Box-and-whisker diagram of GOCM feature values ....................................... 83

5.8 Scatter plots of a random selection of GOCM features ................................... 84

D.1 Non-Defective .................................................................................................. 119

D.2 Blisters ............................................................................................................. 120

D.3 Scratches ......................................................................................................... 120

D.4 Die-Lines ........................................................................................................ 121
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Dedication

To my grandfather
Chapter 1 Introduction

1.1 Aluminium

Aluminium (Al) is the second most abundant metallic element on earth after silicon. 8% of the earth’s crust is aluminium, although not in its pure form it is usually contained in minerals such as bauxite and cryolite. Aluminium’s low density, approximately a third of the density of copper or steel, makes it very popular, along with its corrosion resistance, which is due to the thin layer of oxide that forms on the aluminium surface and protects the rest of the material. These properties; low density, corrosion resistance, non toxicity, high thermal conductivity and electrical conductivity, make it valuable to many applications. Another important benefit of using aluminium is that it can theoretically be recycled up to 100%. Having those properties result in high demand of the material in aerospace, transportation, structural and packaging industries, where it is used in airplane parts, automotive parts, building frames, soda cans, heatsinks etc. The metal was first introduced in 1825 by Danish physicist and chemist Hans Christian Ørsted, but the process to produce it in high quantities was invented in 1886, almost simultaneously, by Charles Martin Hall in USA and Louis Toussaint Héroult in France and was named Hall-Héroult process. Aluminium can be machined, cast, drawn and extruded. In fact, aluminium is one of the most commonly extruded metals, with profiles used in tracks, frames, heatsinks, mullions, pipes, windows etc.

1.2 Motivation and research objectives

The spark for this research came from the industry’s lack of automated visual inspection on the extruded aluminium profile surfaces. While other industry segments are enjoying automated quality control for some decades now, the aluminium extrusion industry was left behind. This is due to the complexity of the problem as defects on the aluminium
surface are very random in nature and cannot be easily quantified. Not all the surfaces of 
the aluminium profiles need to be in pristine condition, as it depends on the application, but 
those profiles, which when installed are visible to the human eye, need to have an adequate 
surface quality void of defects. There is a significant gap in the literature when it comes to 
aluminium surfaces, but there is information on similar materials such as copper or steel, 
especially for strips or sheets. With proper visual quality control the industry will be able 
to save a lot of scrap, which usually result in B grade material, due to contamination. The 
necessity of automated surface quality control is highlighted in Appendix A which consists 
of an interview with Mr Ioannis Kantonias, C.E.O of Exalco S.A a Greek aluminium 
extrusion company.

The aim of this research was to provide the aluminium extrusion industry with means 
to accurately detect defects early in the production stage, even as early as the profiles are 
extruded. The advantage of early detection is to adjust the process parameters in order to 
counter the appearance of defects.

Specific objectives to reach this aim were:

• To investigate aluminium extrusion surface defects and relevant feature extraction 
techniques (chapters 2&3).

• To create a system that acquires images from aluminium surfaces (chapter 4).

• To obtain a sample set from extruded aluminium profiles (chapter 4).

• To improve the established techniques or develop a new one, improving the accuracy 
of the classification (chapters 4&5).

1.3 Thesis layout

Chapter 2 provides information about the extrusion process, the factors that are important 
to maintain a good product quality and those that result in defects. All of the surface defects 
in the literature are discussed with possible causes and effects on the product quality.
Chapter 3 introduces the concept of machine vision in automated visual quality inspection. An exhaustive literature review is performed for identifying efficient methods on defect detection. The literature review is not only narrowed on metallic defects but expanded in other fields in the search for feature extraction. A heavy focus is placed upon gray-level co-occurrence matrices and their statistical features due to their broad acceptance and efficiency in detection in a wide variety of fields. A brief section is dedicated to illumination, which is a decisive factor in automated visual quality inspection.

In chapter 4, techniques in the literature are implemented in example images obtained from aluminium surfaces of real workpieces (not artificial images). Basic techniques were applied first, while gradually moving to the implementation of co-occurrence matrices statistical features. The last section of the chapter discusses a novel implementation of an evolution of GLCM, which will act as the basis for successful classification of defects in the next chapter.

Chapter 5 is separated in two parts. Two case studies with three and four classification targets respectively. Every result obtained using gradient-only co-occurrence matrices is compared to the widely adopted GLCM, while showing that the proposed technique achieves much higher accuracy rates for the complex, near-stochastic textured surface of aluminium extrusions.

In chapter 6, following a summary on the aims and objectives of this research, the novel developed method (GOCM) is evaluated, highlighting its significance. Future directions for research and implementation of gradient-only co-occurrence matrices are provided.

Appendices contain the interview with Mr Ioannis Kantonias C.E.O of Exalco S.A, source code for MVTech Halcon 9.0 and Matlab 2012b, images that were used in the neural networks training and the ethical review.
Figure 1.1: Overview of the Thesis
Chapter 2 Aluminium Extrusion

2.1 Aluminium Alloys

Aluminium alloys are divided in wrought and cast alloys. Wrought alloys are used in extrusions which range from series 1000 to 8000. 1000 series are the purest alloys as they contain at minimum 99% aluminium. 2000 series have copper as their main alloying element in the range of 3-6 wt%. 3000 series contain manganese as their main alloying element (1-2 wt%). 4000 series contain silicon up to 12 wt%. 5000 series contain magnesium up to 6 wt%. 7000 series have as main alloying elements 4-6 wt% of zinc and 1-3 wt% of magnesium. 8000 series contain major alloying elements not included in the other series; many have lithium as the primary alloying element. According to Sheppard [1999], 6000 series of aluminium alloys account for 85% of the aluminium extrusions.

The aluminium 6000 series of alloys have as primary alloying elements Magnesium (Mg) and Silicon (Si), mostly from 0.3 to 1.5 wt%. These are the most used alloys for extrusions today, because they have good corrosion resistance, surface finish, formability and medium strength, thus they can be perfect candidates for architectural sections and structural applications (Figure 2.1). Magnesium silicide (Mg$_2$Si) makes the 6000 series heat treatable and capable of achieving medium strength in the T6 condition. The alloys

<table>
<thead>
<tr>
<th>Alloy</th>
<th>Temper</th>
<th>Formability</th>
<th>Machinability</th>
<th>General Corrosion Resistance</th>
<th>Weldability (Arc with Inert Gas)</th>
<th>Brazability</th>
<th>Anodizing Response</th>
<th>Electrical Conductivity (% IACS at 60°C)</th>
</tr>
</thead>
<tbody>
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<td>T1, T4, T611</td>
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<td>D C B A</td>
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</tr>
<tr>
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<td>T5, T52, T522</td>
<td>Low</td>
<td>CBA</td>
<td>D B A</td>
<td>D C B A</td>
<td>N/A</td>
<td>N/A</td>
<td>50-60</td>
</tr>
<tr>
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<td>N/A</td>
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<tr>
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<td>N/A</td>
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<td>6063</td>
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Figure 2.1: Some of 6000 series alloy characteristics taken from [http://www.buildlog.net/documents/Extruded_Alloy_6063.pdf](http://www.buildlog.net/documents/Extruded_Alloy_6063.pdf)
contain magnesium silicide $Mg_2Si$ as their primary strengthening agent. This must be in solid solution during the extrusion process (Figure 2.2). The billets must be properly homogenized before they are extruded. The process of artificial aging of the extrudate causes $Mg_2Si$ to precipitate, thus providing the required strength characteristics.

Temper 6 means that the alloys are solution heat treated, which is achieved by holding the alloy at a temperature where in the equilibrium diagram one phase condition is reached. This dissolves the precipitates ($Mg_2Si$) in a homogeneous solid solution state, remaining below the melting temperature and avoiding the eutectic temperature. Then by quenching

Figure 2.2: Al – $Mg_2Si$ phase diagram [Zhang et al. 2001]
with forced air the previous state of a homogeneous solid solution is maintained, which is called press quenching. The next step is artificial aging by reheating to a temperature below the dissolution line resulting in an efficient formation of the precipitates. This introduces stresses to the matrix, which act as a barrier against deformation.

Figure 2.3: Buehler microscope image of 6063 alloy billet cross-section at 500x magnification level

At room temperature the amount of $Mg_2Si$ in the alloy is more than what can be soluble, that is why heating is required to allow for more quantity of $Mg_2Si$ to form a solid solution. Precipitation for low alloyed Al-6000 is slow. Strengthening can occur at room temperature over a long period of time. If the aging time is short (at 200°C), then fine needle shaped zones are formed which are approximately 6nm in diameter and 20-100nm in length (Fig 2.3). Uniformity in microstructure is needed; otherwise many shape related problems occur. Magnesium lowers extrudability by increasing the maximum extrusion pressure, increases strength and lowers ductility and toughness. Silicon lowers extrudability if in excess. It is a good strengthenener up to 0.4%. Low concentration of iron improves ductility and toughness,
while being detrimental to the surface finish. Exposure in 500°C – 600°C dissolves the precipitate formed during casting. The hold temperature is a critical factor on extrudability and surface appearance by converting $\beta(Al, Fe, Si)$ to $\alpha$-phase. $Mg_2Si$ needs around 2 hours in temperatures higher than 465°C to dissolve. The surface quality is dependent on the $Mg_2Si$ precipitation. The billets should be cooled from the homogenization temperature with the fastest rate possible, excluding water quenching.

### 2.2 Extrusion

![Diagram of direct and indirect extrusion](http://www.aluminiumdesign.net/design-support/aluminium-extrusion/)

**Figure 2.4: Direct and Indirect extrusion taken from**

Aluminium extrusion is the metal forming process where an aluminium billet is squeezed through the opening of a die, within a metal container, by a ram, achieving the desired cross-section. Extrusion can be hot or cold, direct or indirect. The tool required for this process is called "press" and is usually hydraulic and horizontal for hot extrusion. Depending on the method of extrusion, the process is described as follows:

- Direct extrusion, where the material flow has the same direction as the ram (Fig 2.4).
- Indirect extrusion, where the die is fixed at the front of the ram while moving towards and inside of the material with the resulting product coming out through the ram
• Hydrostatic extrusion, where the metal chamber is flooded with liquid which is compressed by the ram. The generated hydraulic pressure is transferred homogeneous to the billet and causing it to exit through the die.

• Impact extrusion, where the chamber is replaced by a cavity and the material is forced by the high punch speed around the circumference of the punch.

2.3 Defects

The extrusion is a complex process with many variables, some of which can be controlled (e.g. temperature, extrusion speed, lubrication), while some others cannot. The quality of the final product is affected by those variables, thus having different characteristics. Some of those characteristics can cause defects. ISO9000:2008 defines defects as:

\[ \text{The non-fulfillment of intended usage requirements. The departure or absence of one or more quality characteristics from intended usage requirements.} \]

A common type of defect is poor mechanical properties (tensile strength, yield strength, hardness and ductility) of the extruded profile. Often \( Mg_2Si \) precipitates can be encountered in coarse form, not redissolving during the extrusion process, resulting in not allowing the artificial aged product to achieve the maximum mechanical properties. The cause of this can be slow post homogenisation cooling rates, due to which coarse \( Mg_2Si \) precipitates form. Some times profile geometry can deviate from the specifications, this is a defect cause by bad design of the die and / or wear if it. The inhomogeneous deformation caused by nonuniform movement of the billet’s peripheral zones (skin) is called funnel formation. A similar defect, also occurring due to the billet’s peripheral zone, is called back-end defect. This happens after \( 2/3 \)rds of the billet are extruded and the skin is moving towards the centre of the extrusion, which causes an annular separation in the cross section of the extruded product (separating an inner core from an external zone).
2.4 Surface Defects

The surface defects found in the literature are:

- Die-Lines
- Pick-up
- Tearing
- Blistering
- Colour Streaks
- Weld Lines

Some of those defects are exaggerated after anodizing or powder coating. The condition of the die, its quality, extrusion speed and temperature, billet quality and tooling specifications are the most important factors of surface quality (Figure 2.5). There are many applications where absolute quality is needed. Commercial decor strips, usually encountered in mobile phones and other electronic and household equipment, require a pristine appearance void of any defect. Appearance is almost equally important in furniture, shower cabinets, lighting and structural building parts such as doors, windows, ladders.

Aluminium extrusion companies rely on a human eye examination of the profile, rating it depending on the distance the defect is visible under a certain focusing time frame for the inspector. For finer detail the distance is as close as a few decimetres. For not important parts having the distance requirement is raised to be larger than a metre. This archaic approach hasn’t changed and often defects are omitted. According to Schoonahd et al. (1973) visual inspection performed by humans can be very accurate in the case of false positives (2%) but very inaccurate in the case of false negatives (23%).
2.4.1 Tearing

Surface cracking occurs due to high temperature or speed and starts from the edges while developing towards the centre. It is a cause of tensile stress failure at areas of melting (Qamar et al., 2004). Reiso (1984) found that the extrudability of $\text{AlMgSi}$ alloys was reduced by increased cooling rate or increased alloy content. This caused surface cracking due to tearing in the aluminium matrix (Figure 2.6).

2.4.2 Pick-up

Pick – up defects (Figure 2.7) are caused by inclusions in the billet, inadequate homogenization treatment and die deflection (Langerweger, 1982). This defect has the shape of lines of small length (3mm – 12mm) which usually end up in some form of aluminium deposit.
As the extrusion happens, aluminium material is adhering to the material of the die land. This aluminium is building up over time, when finally it separates from the die land and is embedded on the surface of the extruded material. The defect is enhanced by inclusions in the billet, inadequate homogenization treatment and dies deflection [Langerweger 1982]. To reduce the appearance of this defect, various methods were suggested as improving casting procedures or modifying tooling. Nitriding the die is one of them. Billet temperature can be increased from 450°C to 500°C for a reduction in pick-up [Parson et al. 1996].

2.4.3 Die-Lines

Die lines (Figure 2.8) are defined by the Aluminium Association as

“longitudinal depressions or protrusions formed on the surface of the drawn or extruded material due to imperfections on the die surface”

Figure 2.7: Pick-up defect (image taken using Mitutoyo QuickVision)
Die land plays an important role on the surface formation. The front position of the die land is responsible for generating the surface in absence of oxygen, while the rear portion of the die land is uneven allowing oxide formation on the surface. The tests conducted by Sheppard (1999) show that the length of the die land is detrimental to the surface roughness. The optimum length for 6063 extrusion was from 1 – 3mm while the roughness increased by even 200% for 6mm or more of die land length. There is little documented research on die lines, which are believed to be caused by adhesion to the die land surface. Die lines also occur even if the die is polished, but they are finer and shallower, and are called micro–die lines. The effects of those are enhanced during anodizing. There is evidence that the iron phase precipitates ($Al – Fe – Si$) are responsible for the formation of the micro-die lines (Clode and Sheppard, 1990). During extrusion those precipitates align with the direction of flow and become elongated and sheared.

A sub category of Die-Lines are black lines, which are due to the imperfections in the
die or uneven flow which can develop more friction in some areas of the extruded profile. Black lines are burnt surfaces on the profile due to the higher temperatures resulting from higher friction.

### 2.4.4 Blistering

Blistering (Figure 2.9) is a result of entrapped air or lubricants below the surface, that can be trapped during upsetting due to the difference in diameter of the billet and the container. When that spot gets a rise in the temperature (due to friction) the gas expands and forms a blister. A 'burp cycle' is often used to prevent this by removing the ram pressure momentarily after upset to allow the air to escape (Reiso, 1984).
2.4.5 Weld Lines

To produce long sections of extruded profiles billet to billet extrusion is used. When the previous billet’s end is merged with the next billet distinctive sections are formed, which are called weld lines (Figure 2.10). They are transverse to the profile’s length and usually their thickness is different than the rest of the profile. This occurs due to the end of the billet which is contaminated with lubricant and oxidized material thus providing an uneven weld. Weld lines can be longitudinal when hollow sections are extruded (Arif et al., 2002).

2.4.6 Colour Streaks

The texture of the extruded product can alter the light-reflecting properties of it. Lighter or darker bands can be formed, while difficult to spot with naked eye; they can affect the anodizing effect considerably, by altering the tone of the colour (colour streaks). Those
bands can appear darker or lighter, brighter or duller in colour and tone than the rest of the surface (Arif et al., 2002). This is usually spotted after the anodizing and can lead to a lot of scrap when the application requires good quality of surface finish (architectural applications like frames for windows). The crystal orientation, the grain structure and the particle distribution can be altered as an etching response of the anodizing process.

2.5 Surface Quality and Extrusion Parameters

There are many factors that affect the surface quality of the extruded product. Many of those were described previously in each defect category. According to Parson et al. (1996) the most important are:

**Figure 2.11: Surface finish dependance**
• The quality of the surface finish deteriorates to a minimum at a critical exit speed that is dependent on the billet temperature.

• Using lower extrusion speeds the surface quality increases at the cost of productivity.

Figure 2.11 shows the process parameters found in the literature which affect the extruded product’s surface finish.

### 2.6 Summary

This chapter contains a literature review on aluminium alloys, the extrusion process, the resulting surface defects and the conditions for their appearance. This research focuses on aluminium 6000 series alloys which containing Magnesium and Silicon as their main alloying elements. Due to the various parameters affecting the quality of the finished product, defects can appear. Problems occur in the form of deviating dimensional tolerances, poor mechanical properties or surface defects. The surface defects encountered in the literature are Die-Lines, Pick-up, Tearing, Blistering, Colour Streaks and Weld Lines. The condition of the die, extrusion speed and temperature are some of the most important extrusion parameters. The next chapter will contain information on automated visual quality inspection.
Chapter 3 Automated Visual Quality Inspection

3.1 Machine Vision

Machine vision is the application of computer vision to industry and manufacturing. One of the most common applications of machine vision is the inspection of manufactured goods ranging from food to semiconductor industries. The key components to a machine vision system are digital cameras, computers (or embedded processors) and software to perform image processing. The high speed, 24/7 operation and the repeatability of the results makes these systems ideal to replace the traditional visual inspection performed by people.

3.1.1 Digital Camera Types

Digital cameras are the devices which capture an image from the light focused in the image plane by the lens. There are two main digital sensor technologies: CCD (charge-coupled device) and CMOS (complementary metal-oxide-semiconductor). Both types of sensors convert light into electric charge and process it into electronic signals. CCD sensors transfer the charge from the photo detectors row by row into the serial readout registers and then they are read out sequentially through the charge converter and amplifier. CMOS sensors have amplifiers for each pixel, and enable read out directly through the row and column select circuits.

The interfaces typically used by digital cameras are:

- Camera Link
- FireWire
• Universal Serial Bus 2.0

• Gigabit Ethernet

3.1.2 Images

An image is transferred to the computer as an array of w x h numbers (where w width, h height, which forms the camera’s resolution). Each pixel is represented by one or more values (depending if the image is monochrome or colour). The scale used to give a value to a pixel is called bit depth (a typical 8bit gray-scale bit depth corresponds to gray values of 0 to 255).

3.1.3 Obtaining Information

According to [Malamas et al. (2003)] the (optical/vision) inspection system computes information from images following the sequence (Figure 3.1):

• Image acquisition. With the use of cameras images are converted into digital form.

• Image processing. The images are manipulated in a way to avoid unnecessary characteristics such as noise or reflections.

• Feature extraction. Regions of interest are segmented from the image, quantified and measured. They can be analyzed by statistical techniques, neural networks or fuzzy systems.

• Decision-making. According to the classification, tolerances or quality standards the segmented ROIs are accepted or denied.

![Figure 3.1: Inspection sequence](image-url)
3.2 Literature review of pattern recognition techniques

Machine vision is tailored to the particular inspection application, thus the possibilities of integration are endless. Over the past two decades many machine vision systems have been installed in different areas for quality inspection. Aluminium extrusion surface quality control is one area lacking significant research in quality control automation. Reflective surfaces, like metallic ones, require special approach as the reflections of the surface mask important information. When searching the literature for information on one specific subject one must keep an open mind and look what is proposed and tested in other areas, such as satellite imagery, fabrics, cork, medical applications, PCB inspection. A variety of different approaches is often suggested, with many that give excellent classification accuracy but with considerable drawbacks (one of which is computational time, but this is soon alleviated by the advances in microprocessors). Newman and Jain (1995) have written an exhaustive survey on the subject of automated visual inspection, separating the research done in binary image based, intensity, color and range based, defining inspection as:

"The process of determining if a product deviates from a given set of specifications"

A good proportion of the research on automated visual inspection is based on extracting information of the textured surface of the samples, leading to a number of techniques suitable for texture analysis and classification. A recent survey by Xie (2008), categorizes the methods of textural defect detection in statistical, structural, filter based, model based and colour texture analysis. He concludes that the largest portion of textural defect detection is based on statistical and filter methods and suggests that there is a clear need of some standard datasets evaluating the performance of different methods. A more recent review by Ortiz-Jaramillo et al. (2014) evaluated different texture classification methods, commonly used by researchers in the field, and provided results with good evidence that power spectrum, local binary patterns, the texture spectrum, Gaussian Markov random
fields, autoregressive models and the pseudo-Wigner distribution are good measures of fine changes in global texture.

### 3.2.1 Classification of metallic surfaces

This research deals with the quality control on aluminium profiles. The importance of the surface is not only crucial for unpainted application but also after the profile has been treated with a coating, as a presence of defects can alter the desired appearance and quality of the paint. [Montero-Moreno et al. (2007)](#) discuss how critical the aluminum surface is for the anodizing. They used a 5 step procedure that involved alkaline degreasing, alkaline etching, desmutting, galvanostatic electropolishing and acid etching, concluding that the best alumina layers were formed when the maximum anodizing potential reach its highest values. The need to automate the quality control process has always been critical with attempts to introduce complete and reliable systems as early as the nineties, when [Fernandez et al. (1993)](#) developed a prototype of an automated machine vision system for detecting defects in aluminum castings. Although the research doesn’t provide results, they support the idea to classify the segmented defective areas by means of shape and a defect decision tree is employed, classifying them according to orientation, gray values and size properties. 20 years later, [Swillo and Perzyk (2013)](#) revisited surface casting defects of aluminium, combining Gaussian and Laplace filters to convolve the image, resulting in possible defective areas. From the segmented defects they measured 8 attributes using blob analysis and input them in a neural network, which they claimed to be 90% accurate for 3 defect classes, blowholes, shrinkage cavity and shrinkage porosity. Other researchers too have used blob analysis techniques, like [Shafeek et al. (2004)](#), who have written their own program in Microsoft Visual C++ for assessing defects in radiographs of welds. Their method consisted of the following steps: histogram stretch, histogram equalization, median filter, histogram specification, thresholding, chain code algorithm, defect extraction. Finally they were able to measure the area, perimeter, length and width of the defects with camera calibration (each pixel corresponded to 123 $\mu$m). Still on the subject of blob analysis
and morphological operations, Zheng et al. (2002) approached the inspection of metallic surface defects, with 91% accuracy for hole defects and 86% accuracy for crack defects, using Genetic Algorithms in combination with median filter, closing top-hat operation, segmentation threshold operation and noise removal via elimination of areas smaller than a defined value. Garbacz and Giesko (2013) presented a paper on the inspection of aluminium extrusion using infrared thermography. Without publishing results, they discussed about possible ways of detection with a heavy emphasis on surface temperature distribution obtained by an infrared camera, while providing references to different methods from the literature for different defects.

Aluminium metalworking wasn’t the only industry requiring surface quality control. Jia et al. (2004) developed a defect detection system for the steel industry capable of detecting a defect faster than 6msec in an one megabyte image. They used a rough filtering algorithm based on a horizontal gradient operator to detect the edges of the seams on the hot rolled steel. Support Vector Machine algorithms were trained to learn complex decision boundaries in presence of noise. Caleb-Solly and Smith (2007) have created an adaptive surface inspection system via interactive evolution. It is applied in the hot-rolled steel industry. Amongst the techniques they used are image segmentation, Self Organizing Map Neural Network, Multi-Layer Perceptron classifier and Evolutionary Algorithms. Lee et al. (1996) used an Adaptive Wavelet Packet algorithm to extract 14 features from images of cold rolled steel strips containing 8 classes of defects. These features are derived from the entropy of the images and sub bands of the wavelet decomposition, while initially 64 in number, they are reduced through the algorithm using a decomposition measure based on the variance of the sub band. From 387 images used for training and testing divided almost evenly, the resulting accuracy was 99%.

Copper is amongst the most used metals, particularly due to its excellent electrical conductivity matched only by silver, but at a much more affordable price point, making it ideal for consumers. Recent advances in defect detection in copper strips include a research by Liang et al. (2008), who used Pseudo Zernike polynomials moments (scale
invariant central moments and radial geometric moments) as features for a SVM based on RBF activation function. They extracted the six defects and proliferated the training images rotating the original. The total accuracy rate was 92.9% for the BP optimized SVM-RBF-NN and 87.8% for the traditional RBF-NN classifier. Still on the subject of copper strip defects, another group of researchers modified a technique based on moment invariants by Hu (1962), to better satisfy zoomed invariance, transforming the initial 7 moments in 10 features that were arithmetic calculations of combinations of the initial moments (Ping et al., 2008). Their sample set was 288 images of 6 defects and with use of BP neural networks they achieved recognition rates ranging from 88.9% to 96.3%

Xue-Wu et al. (2011) developed a system for inspection of surface defects on strongly reflective metals, using copper strips as the application of their research. They used wavelet transformations along with Sobel filter and thresholding to obtain five features from texture spectral measures. The classification was done with a Support Vector Machine and produced accuracies that ranged from 76.8% to 91.3%.

Thresholding techniques are widely used in the literature to segment regions of interest. It is a technique that is widely used for automated visual inspection of defects. In real world inspection problem defects either exist or not, they can be small or large, creating a diversity not easily countered by the thresholding techniques. One of the widely used automated thresholding technique is the Otsu method (Otsu, 1975). Ng (2006) wasn’t satisfied with the results this method provided for small defects, so he modified it developing the valley-emphasis method. Especially for scratches in metal sheets the valley-emphasis had 0.006 misclassification errors while Otsu had 0.192.

The methods usually encountered in the literature for automated visual inspection of metallic surfaces are histogram properties, co-occurrence matrices, local binary pattern, morphological operations, spatial domain filtering and frequency domain analysis (Neogi et al., 2014). When the defects are defined and their properties (geometrical) are predicable, then morphological operations (blob analysis) is often used to segment and return features describing the shape of the defective area. When the defective properties cannot be easily
defined, texture based methods are used; first and second order statistics that can provide features that describe the defective area. Especially in the case where segmentation of the defect is problematic, texture based methods and spatial and frequency domain filtering is mostly used.

### 3.2.2 Classification of other surfaces

Moving away from the metalworking industry, on the subject of fabrics, Kumar (2008) has surveyed 166 sources for computer vision based defect detection and classification, providing an exhaustive review on the different methods used to approach classification. Such methods for fabric defect detection are also reviewed by Shanbhag et al. (2012) and Ngan et al. (2011). The methods used are common with the ones used for metallic surfaces and include the statistical approach, the spectral approach and the model-based approach. Statistical methods are divided in auto-correlation, co-occurrence matrices, mathematical morphology and fractal method, while spectral methods are divided in fourier transform, wavelet transform, gabor transform and filtering approach. Rates of success achieved are in many cases higher than 90% accuracy obtained using methods from all categories.

Classification techniques are also employed widely in the Integrated Circuits field, where automated machine vision systems inspect for defects, such as incomplete solder joints, missing components. Zhou et al. (1998) developed an algorithm for detecting die extrusion defects in IC packages. They were unsatisfied by the results of the conventional techniques for image smoothing and removing noise (such as Gaussian filter), so they developed an optimal convolution filter suitable for the application (improving a technique by Petrou (1993)).

The problem of finding defects in directional textures was approached by Tsai and Hsieh (1999) using the Fourier Transform, the Inverse Fourier Transform and the Hough Transform to remove the texture pattern (lines) from the image, in order to isolate the defect from the texture. Their method proved to be robust when compared to feature-extraction method and Gabor-filtering method, but only when applied to directional textures. Tsai
and Huang (2003) presented a technique for defect detection, but not of classification, on statistical textures, using the Fourier Transform, claiming the spread of frequency components in the power spectrum space to be isotropic and approximately form a circle. By selecting a proper radius and setting all components outside of it to zero, they removed the texture pattern using the reverse FT, resulting in non-textured images that could be simply thresholded. A very difficult task was for Tsai and Chao (2005) to detect defects in sputtered glass surfaces, since the nature of the surfaces is random so anomalies are observed. They developed an improved anisotropic diffusion scheme, specifically tailored for detecting defects, which smooths the background texture and preserves those anomalies of the inhomogeneously textured surfaces. The anisotropic diffusion scheme was first presented by Perona and Malik (1990). Their method was superior than Gaussian and median filters, because it didn’t falsely detect defects in clear surfaces and was also accurate at detecting defects in defective surfaces without including too many noisy pixels. The same technique (anisotropic diffusion) was used by Tsai et al. (2010) for the inspection of micro-cracks in heterogeneously textured solar wafers. They modified the approach by subtracting the diffused image from the original gray-level image. Their earlier approach was to smooth the original gray-level image and enhance the defective region in the diffused image.

Brzakovic and Vujovic (1996) studied methods of web material inspection, while suggesting cortical projections of defective regions to be used for feature extraction. Amongst the features used are a measurement for roundness, object orientation and least mean square error fit (object shape), resulting in an average of 85% correct classification.

### 3.2.3 Statistical texture approaches

Perhaps one of the most used techniques for texture classification is the extraction of gray level co-occurrence matrix statistics. Haralick et al. (1973) suggested 14 textural features which could be extracted from gray-tone spatial-dependence matrices (GLCM). Their research is considered a hallmark in texture analysis and classification and is used by many
researchers in the field. Amongst those features were the extensively used Angular Second Moment (Energy), Contrast, Correlation, Inverse Difference Moment (Local Homogeneity) and Entropy. Haralick published a review on the statistical and structural approaches to texture (Haralick, 1979). On that research paper, he presents the most common features computed from co-occurrence matrices, which are Energy, Entropy, Maximum Probability, Contrast, Inverse Difference Moment and Correlation, claiming that they carry much of the texture information, which can be generally applied to a lot of classification problems. He references Weszka et al. (1976) to validate the claim that co-occurrence probabilities have much more information than autocorrelation.

GLCM texture statistics have been used by many researchers in the field of pattern recognition, but most of the times they were used arbitrarily without evaluation of the changes in the bit depth, and even used in groups that had overlapping information. Clausi and Jernigan (1998) investigated the computational load for calculating GLCM from different gray level scales of the original image, and then proceeded to verify the accuracy of a classification problem using different gray levels. Perhaps, the most interesting part of the research paper, is the classification accuracy comparison of individual co-occurrence statistics on gray level scales that vary from 4bit to 8bit. The individual testing resulted in identifying that Maximum Probability, Uniformity, Entropy and Correlation provide better accuracy the lower the bit scale, while Dissimilarity is constant amongst different bit scales and Contrast, Inverse Difference and Inverse Difference Moment provide better accuracy the higher the bit scale. They conclude their research claiming that:

"Textures that have noticeable, but subtle differences at full dynamic range may become statistically similar under coarse quantization".

On a follow-up research of the significance of individual GLCM statistics, Clausi (2002) further investigated the impact of gray levels on the statistics and the accuracy they provide for a classification task. He compared individual statistics between each other and between groups of them. Concluding he suggested that a preferred statistic set is Contrast, Entropy and Correlation with gray level scale greater than 4bit and not necessary greater than 6bit,
since it didn’t improve the classification accuracy while being more computationally costly. An important contribution on the proper selection and importance of GLCM statistical feature parameters selection was from [Venkat Ramana and Ramamoorthy](1996), who suggest that the proper distance "d" to calculate co-occurrence matrices for machined metallic surfaces is 1, which they "felt" that the texture discrimination is best at that value. They compared values obtained from GLCM, Amplitude Varying Rate Statistical approach and Run Length Matrices, concluding that they could all be suitable for texture classification, especially indicating surface roughness.

### 3.2.4 Gray level co-occurrence matrix features

GLCM statistical features were used in the literature with success in various classification tasks. [He et al.](1988) developed a criterion for selection of features derived from GLCM, Spectral peaks and Radial/angular distribution of the energy. The total number of features was 173 while the algorithm (based on LDA and Exhaustive Search Feature Selection) selected 10 of those as the best for the classification of Brodatz’s texture images ([Brodatz](1966) with an accuracy of 94.7%. The sample size was 640 images of 10 texture classes and when additional features were added the error rate increased.

GLCM statistical features can be applied not only on the original image but in some version of it after processing, like [Latif-Amet et al.](2000) did when they combined Wavelet Transform and GLCM to extract co-occurrence features from the highest energy sub band of the Wavelet Transform. With a data set of 36 256 x 256 pixel images, 19 of which were defective, the best results obtained were 90.78% using a 32 x 32 sized non-overlapping sub-windows.

The application of GLCM statistical features is very important to classify aerial / satellite images, since this is the area of expertise where most of the literature is based. [Zhang](2001) dealt with the problem of classifying urban treed areas in color colour – infrared images. He concentrated his research on the variance feature from GLCM and developed a method to use Directional and Local variance to categorize edges that belong to treed
areas separately from those that belong to buildings and streets. His results were a massive improvement over the common approach of multispectral classification, increasing accuracy rates from 61% to 97% for a sample area of 1500 by 2000 pixels for Berlin and 1000 by 1500 pixels for Duisburg. Another research project was challenged with cloud detection in remote sensing images [Changhui et al., 2013]. The method employed features from gray-scale feature vectors, frequency feature vectors and texture feature vectors (GLCM). They used 1024 images of 64x64 pixels as the training set and divided 30 satellite images of 1024x1024 in sub-images of 32x32 which resulted in 30720 sub-images. Each of the sub-images was classified as cloudy or non-cloudy and was assigned a binary value which, when reconstructed, gave a binary image of 1024x1024 that contained information about the cloud coverage of the initial image, having an accuracy of around 90%.

Moving further away from the satellite imagery, in heavily textured materials such as cork types, rock textures, many important contributions are made the last decade. Georgieva and Jordanov (2009) investigated a sample dataset of 700 cork tiles, which were used to produce a set of 33 features, using co-occurrence matrices measures and Law’s filter masks. Due to the dimensionality of the problem principal component analysis (PCA) and linear discriminant analysis (LDA) techniques were used and compared to reduce the dimensionality of the problem, along with GLPτS training method for neural networks to produce a testing success rate of up to 95% for 7 different sample classes. A further investigation by Petrov et al. (2013), using part of the same dataset and additional features such as Entropy, tested the performance of Self-organizing maps with rates up to 88% on PCA and 98% on LDA. On the subject of corks, Oliveira et al. (2013) used stepwise discriminant analysis to build predictive classification models to characterize the surface of cork stoppers and cluster them into three quality classes and analyze the contribution of each porosity feature to the class classification. Ershad (2012) developed a technique based on Local binary pattern and GLCM, followed by edge extraction to retrieve statistical features from images of stone textures. Seven features were used, Entropy, Energy, Contrast, Homogeneity, Correlation, Mean and Variance, which provided results with an accuracy of
93% compared to the 88% and 86% achievable from LBP and GLCM respectively. His sample size was 60 images divided evenly for 3 different classes of stone texture.

### 3.2.5 Gray level gradient co-occurrence matrix features

A not widely adopted variation of the GLCM statistical feature method of classification is the GLGCM technique, where features are extracted from the gradient of the original image. A pioneer of the method, Wang-Cheung Lam, presented an approach for feature selection and extraction using gray level gradient co-occurrence matrices. He defined seven new features to be used: *Edge Strength, Intensity Symmetry, Geometric Symmetry, Magnitude Difference, Gradient Magnitude, Diversity and Concavity* (Wang-Cheung Lam, 1996). A comparison of different texture images was completed on a numerical level showing the difference in feature values among four texture images (woven aluminum wire, pressed cork, beach sand and water). He then concluded that, since Intensity Symmetry and Geometric Symmetry didn’t differ a lot, they are insignificant.

This method is not only used for classification, but has benefited segmentation problems like medical image segmentation. HongQing (2004) presented a method for segmentation of blood vessels in retinal images. The method involved use of Sobel operator to obtain the gradient of the image followed by a co-occurrence matrix of that gradient which was partitioned in quadrants, each possibly showing class, background class, edge and background and edge. Using the entropy of the image, the method needed a threshold vector which maximized an equation describing the relationship between different quadrants to perform the segmentation. Concluding the method needed extra pre-processing to eliminate non-vessel objects.

Another interesting usage of the GLGCM statistical features technique is the prediction of properties. Wang and Dong (2009) presented a paper based on feature extraction from gray level co-occurrence matrices and gray level gradient co-occurrence matrices to analyze gas/liquid flow images. Their method involved extracting seven features from GLCM and fifteen features from GLGCM which were correlated to the four kinds of flow images.
with different superficial gas velocity and gas/liquid density ratio. They concluded that the features could be used in flow regime recognition, while some of them will reflect the content of gas and possibly be feasible in gas volume fraction measurement.

Not only textured objects are benefited, but Chen et al. (2009) extracted features through gray level gradient co-occurrence matrices in the neighborhood of interest points for scene classification. Their method involves Interest point localization which used a Difference of Gaussian function to identify potential interest points, Feature vector extraction based on GLGCM, Interest point descriptor which is formed from a vector containing the values of all the statistical features of GLGCM and Similarity matching based on Gower’s similarity coefficient (Ye and Xu, 2004). Their results compared with other authors showed similar accuracy rates (from 85% to 91%) for 5 different scenes to the SIFT (Lowe, 2004) approach.

Another group of researchers, Fang-fang et al. (2011), used features from gray gradient co-occurrence matrices in a back propagation neural network for the recognition of oceanic internal waves. According to their experiments the images were divided into subgraphs of 100x100 from which, using the GLGCM, five features were obtained, big grads dominance, gradient average, gray mean square deviation, gray entropy and hybrid entropy. The results had an accuracy of 90.6% for internal waves and 83% for no internal waves. Stripe clouds were a problem for the recognition rates as they claimed.

### 3.2.6 Illumination

In a classification task where images are obtained through imaging equipment illumination is crucial in the quality of the information received from the image. Pernkopf and O’Leary (2003) focused their research on the illumination side of image acquisition for automatic visual inspection of metallic surfaces, showing three imaging techniques. The first is intensity imaging which includes front lighting, back lighting and structured lighting, depends on the reflectivity of the metallic surface and the chosen illumination setup, and is based on the gray level intensity data. Range imaging is the next, which depicts the height information of the image objects, while needing more steps than intensity imaging to
retrieve the depth data. Range imaging consists of two separate techniques, light sectioning, involving a light plane projected onto the object from one direction and a camera from a different angle, and photometric stereo, involving multiple cameras and light sources to reconstruct a 3D image, which with proper calibration can be measured.

3.3 Summary

This chapter contained a literature review of automated visual quality inspection. The stages required for a machine vision system are; image acquisition, image processing, feature extraction and decision-making. Machine vision has been applied to different fields from metallic products to the food industry. There is a vast collection of techniques employed in the field of automated visual quality inspection. The focus of this research is the texture based feature extraction approach, specifically co-occurrence matrices and their statistical features. A texture based approach according to the literature fits the purpose of defect detection on the surfaces of extruded aluminium profiles as similar techniques have been used in metallic surfaces. Furthermore the defects on the surface cannot be easily defined morphologically since they can occur in a wide variety of shapes and sizes. Still, as evident by the literature, there is no correct way of approaching any particular problem and many different methods can be used with similar results. In the next chapter image processing and feature extraction techniques, that were discussed in this chapter, will be applied and improved for this particular research.
Chapter 4 Image processing and feature extraction

4.1 Machine Vision Introduction

Machine vision is a relatively recent development in quality control of manufactured products. It begun spreading in manufacturing companies during the 1980ies and today is a standard practice in many manufacturing processes. It involves capturing an image or video of the product and/or process with the objective of analysing and manipulating it. Machine vision is a combination of several different types of equipment such as optics, lighting, software and electronics. The purpose of its development is for controlling processes or quality control. It often leads to a better product quality as it enables (in most cases) 100% quality check. It also leads to lower production cost eliminating (to a certain extend) the appearance of defects, which involves savings in the materials used, production capacity used and transportation costs. Sometimes it can also be set-up in a way that feeds the information back in a way that the process parameters are changed and lead to a better product.

4.1.1 Image enhancement

Sometimes, even the best hardware and the correct illumination don’t provide the result needed to process the image, when important information is masked by noise or reflections. The process of transforming the image to provide better information is called image enhancement.
4.1.2 Gray-level value transformations

Two typical adjustments are brightness and gamma. If we want to represent those adjustments using mathematical formulae then:

For brightness:

\[ f(g) = g + b \] (4.1)

For gamma:

\[ f(g) = a \cdot g \] (4.2)

A combination of both results in:

\[ f(g) = (a \cdot g) + b \] (4.3)

Where \( f(g) \) is a function that defines the gray-level value transformation. \( a \) is the gamma adjustment and for \( |a| < 1 \) the contrast is decreased while for \( |a| > 1 \) the contrast is increased, but if \( |a| < 0 \) then the gray values are inverted. \( b \) is the brightness adjustment and for \( |b| > 0 \) the brightness is increased while for \( |b| < 0 \) the brightness is decreased. \( g \) is one gray-level value.

4.1.3 Image smoothing

In order to retain the important patterns in the image and remove the noise (random changes in the gray values) we need to use image smoothing operators. Such an operator can be a filter which transforms one image into another image. Various techniques can be employed such as temporal averaging, spatial averaging, Gaussian filtering, median calculation etc. (Huang et al., 1979; Steger et al., 2008). For image smoothing, the techniques that can be used include the following:

- Anisotropic diffusion (Jahne et al., 1999; Perona and Malik, 1990; Weickert, 1998)
- Gaussian filter
• Mean filter

• Median filter

![Figure 4.1: Image smoothing using different techniques](image)

As seen in Figure 4.1, the anisotropic diffusion smoothing techniques provide a texture removal while preserving the edges. Amongst the others, the differences are minimal to the naked eye for the current picture. The mean filter is preferred when the speed of the application is crucial while the Gaussian filter produces better results with larger filter sizes (Steger et al., 2008). According to Lindeberg a good smoothing filter should have the following characteristics (Lindeberg, 1993):

• It should be linear.

• It should be position-invariant.

• It should be rotation-invariant.

• One should be able to control the amount of smoothing.

• One should be able to perform the smoothing several times in succession.
4.1.4 Image segmentation

The process of removing unnecessary information from the picture is called Image Segmentation. The input is the original picture and the output is one or more regions of interest. The simplest method to do that is with the thresholding technique (Ballard and Brown, 1982; Forsyth and Ponce, 2002; Hornberg, 2007). It selects the pixels between two gray values. All the pixels within the threshold get a value of one while the others get a value of 0, thus essentially transforming the image into a binary one. Thresholding results of the blister defect are seen in Figure 4.2.

The above pictures are binary images. Thresholding returns binary type of images which means they only consist of two values of colour. It is easier and less computation extensive to process binary images since they contain less information and the data are lower in size (bits). In this example the blisters were separated from the rest of the unnecessary information in the image using a typical pixel precise threshold and a sub-pixel precise one. Sub-pixel precision is used when a higher accuracy is required. The result is a typical thresholding, as a region, while sub-pixel precise thresholding return contours, which represent the boundary between regions in the image. This is a result of thresholding smoothed images.

Due to the smoothing the threshold wasn’t as accurate as the original picture. On the other hand for the sub-pixel precise threshold the anisotropic diffusion smoothed image provided the best accuracy (Figure 4.3).
4.1.5 Edge extraction

The drawback of thresholding is that it depends on illumination. A sudden change in illumination provides different results, thus the accuracy is not always the required one. The best way to describe the boundaries of the objects robustly is to regard them as edges. Edges are the dark - light transitions in the image. The traditional way of finding edges is to apply an edge filter. These filters have the effect to find pixels at the border between light and dark areas. An edge in a two-dimensional image can either be defined if the directional derivative in the direction perpendicular to the edge is locally maximal, or considering the edge as the zero crossing of the Laplacian. To detect those edges specialized filters are used, some of which include the following (Forsyth and Ponce, 2002; Gonzalez and Woods, 2002; Pratt, 1991):

- Sobel (Sobel, 1990)
- Canny (Canny, 1986)
- Deriche (Deriche, 1987a,b, 1990)
- Lanser (Lanser and Eckstein, 1992)
• Shen (Castan et al., 1990)

• Frei

• Kirsch (Kirsch, 1971)

• Prewitt (Prewitt, 1970)

• Robinson (Robinson, 1977)

• Roberts (Roberts, 1965)

Examples of the above filters are shown in Figure 4.4. As observed, both filters provide acceptable results for the detection of the edges. It seems that the Canny filter provides thinner edges than the Sobel one.

The next step for edge detection is to threshold those images in order to get a binary image of the extracted edges. The thresholds need to have different minimum and maximum values for different filters because the grey values differ. Example thresholds are shown in Figure 4.5.

Figure 4.4: Edge extraction of blisters

Figure 4.5: Thresholds of image gradients
After thresholding the image amplitudes of the edge detectors a skeleton operation will provide the contour of the defects (Figure 4.6). A skeleton is essentially a thinning operation of a shape, much like drawing a shape manually by hand using a single line.

For the images smoothed with anisotropic diffusion and mean filter techniques, using the same procedure as before, we obtain the edge amplitudes shown in Figure 4.7. As observed most of the noise was eliminated from the image from the smoothing operations. Anisotropic diffusion smoothed images have superior noise reduction. After the acquisition of the edge amplitudes of the images, the next operations are thresholding (Figure 4.8) followed by a skeleton operation (Figure 4.9).
Dilation and erosion are two morphological operations which result from Hermann Minkowski’s addition of geometrical shapes (Hornberg [2007], Van Droogenbroeck and Talbot [1996]). They are defined by the following mathematical expressions when applied to binary images:
Dilation:

\[ A \oplus B = \bigcup_{b \in B} A_b \]  \hspace{1cm} (4.4)

Erosion:

\[ A \ominus B = \bigcap_{b \in B} A_{-b} \]  \hspace{1cm} (4.5)

Where \( R \) is the binary image, \( S \) is the structuring element, \( s \) is a vector. After computing the skeletons of the thresholds, the resulting contours are manipulated to the desired shape to look like blisters. Blisters have circular or elliptical shapes usually, so a simple operation would be to dilate the skeleton with a structural element that is a circle or an ellipsis. For this example the circle will be used as a structural element because it is simpler than the ellipse in its definition and less computing intensive (Figures 4.10 and 4.11).

Dilation and erosion for gray-scale images are defined by the following equations:

\[ (f \oplus b)(x) = \sup_{y \in E} [f(y) + b(x - y)] \]  \hspace{1cm} (4.6)

\[ (f \ominus b)(x) = \inf_{y \in B} [f(x + y) - b(y)] \]  \hspace{1cm} (4.7)

where \( f(x) \) is the image, \( b(x) \) is the structuring element and \( B \) is the space that \( b(x) \) is defined.

(a) Sobel  \hspace{1cm}  (b) Canny

*Figure 4.10: Dilations of Figure 4.6*
4.1.7 Fitting of geometric primitives

The fitting of geometric primitives is a very important method of fitting lines, circles, ellipses to the image thus eliminating possible noise and providing robust results (Ahn et al., 2001; Joseph, 1994). The contour data is obtained with the use of the software and subsequently a geometric primitive is fit to the contour data (a circle) (Figures 4.12 and 4.13). The unsmoothed image with Sobel edge detector provides 11 possible blisters. The unsmoothed image with Canny edge detector provides 10 possible blisters. The anisotropic diffusion smoothed images with Sobel and Canny edge detector provide 8 and 7 possible blisters respectively. The mean filter smoothed images with Sobel and Canny edge detector provide 9 and 9 possible blisters respectively. As it can be observed from the pictures the different colours represent different blisters, which make it easy to count both by eye or by the program counting contours. For presentation purposes an overlay can be made with the original picture and the contours of the circles, while also the outer circle of the possible blisters can be displayed for aesthetic reasons. The crucial blisters in the original picture are 9 (Figure 4.14).
Figure 4.12: Fitting of circle (1.5px radius) on the dilations of Figure 4.10

(a) Sobel  
(b) Canny

Figure 4.13: Fitting of circle (1.5px radius) on the dilations of Figure 4.11

(a) Anisotropic Diffused Sobel  
(b) Anisotropic Diffused Canny  
(c) Mean filtered Sobel  
(d) Mean filtered Canny

Figure 4.14: Two blister detection results using different techniques

(a) Incorrectly detected possible blister (red circle inside green one) using non-smoothed Canny edge detection  
(b) All crucial blisters detected using mean filter smoothed Sobel edge detector


4.2 Image acquisition

4.2.1 Extruded aluminium profile sample set and hardware equipment

For the purposes of this research there were no artificial images created. All the samples used were obtained from an extrusion facility owned by EXALCO S.A., an aluminium extrusion company located in Larisa, Greece. The set consisted of samples of different profile types suitable for architectural applications. The samples were either 6061 or 6063 alloy series. They had a variety of defects with the most common being blisters, scratches and die lines. The rest of the defects were encountered very rarely in the production line rendering the acquisition of them for a significant sample size impossible, thus they were excluded from the detection and classification testing. A sample picture of a profile’s surface is shown in Figure 4.15 and the actual sub-images used in Appendix D. For image acquisition a Basler Scout scA1000-32gm GigE industrial machine vision camera was used. The camera was connected to a standard desktop PC using gigabit ethernet interface (GigE) with a Cat5e unshielded twisted pair (UTP) cable. The specifications of the camera are included in Figure 4.16. The desktop PC used for image acquisition was an Intel Core 2 Duo with a clock speed of 3.2GHz and 4 Gigabytes of RAM. The desktop PC used for image processing and classification was an Intel Core i7 4770k quad core processor with a clock speed of 4.2GHz and 16 Gigabytes of RAM.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resolution (H x V pixels)</td>
<td>1296 px x 956 px</td>
</tr>
<tr>
<td>Pixel Size horizontal/vertical</td>
<td>3.75 μm x 3.75 μm</td>
</tr>
<tr>
<td>Frame Rate</td>
<td>32 fps</td>
</tr>
<tr>
<td>Mono/Color</td>
<td>Mono</td>
</tr>
<tr>
<td>Interface</td>
<td>GigE</td>
</tr>
<tr>
<td>Video Output Format</td>
<td>Mono 8, Mono 16, Mono 12 Packed, YUV 4:2:2 Packed, YUV 4:2:2 (YUYV) Packed, RGB 8 Packed</td>
</tr>
<tr>
<td>Pixel Bit Depth</td>
<td>12 bits</td>
</tr>
<tr>
<td>Synchronization</td>
<td>• external trigger</td>
</tr>
<tr>
<td></td>
<td>• software</td>
</tr>
<tr>
<td>Exposure Control</td>
<td>• programmable via the camera API</td>
</tr>
<tr>
<td>Housing</td>
<td>box</td>
</tr>
<tr>
<td>Housing Size (L x W x H) in mm</td>
<td>73.7 x 44 x 29</td>
</tr>
<tr>
<td>Housing Temperature</td>
<td>0 °C - 50 °C</td>
</tr>
<tr>
<td>Lens Mount</td>
<td>C-mount</td>
</tr>
<tr>
<td>Digital Input</td>
<td>2</td>
</tr>
<tr>
<td>Digital Output</td>
<td>4</td>
</tr>
<tr>
<td>Power Requirements</td>
<td>12-24 VDC</td>
</tr>
<tr>
<td>Power Consumption (typical)</td>
<td>3.5 W</td>
</tr>
<tr>
<td>Weight (typical)</td>
<td>160 g</td>
</tr>
<tr>
<td>Conformity</td>
<td>• CE</td>
</tr>
<tr>
<td></td>
<td>• RoHS</td>
</tr>
<tr>
<td></td>
<td>• GentCam</td>
</tr>
<tr>
<td></td>
<td>• GigE Vision</td>
</tr>
<tr>
<td></td>
<td>• IP60</td>
</tr>
<tr>
<td></td>
<td>• FCC</td>
</tr>
<tr>
<td>Sensor Vendor</td>
<td>Sony</td>
</tr>
<tr>
<td>Sensor Name</td>
<td>ICX445</td>
</tr>
<tr>
<td>Sensor Technology</td>
<td>Progressive Scan CCD, global shutter</td>
</tr>
<tr>
<td>Shutter</td>
<td>global shutter</td>
</tr>
<tr>
<td>Sensor Size (optical)</td>
<td>1/3 inch</td>
</tr>
<tr>
<td>Sensor Type</td>
<td>CCD</td>
</tr>
<tr>
<td>Sensor Size (mm)</td>
<td>4.86 mm x 3.62 mm</td>
</tr>
</tbody>
</table>

### 4.3 Image processing

#### 4.3.1 Image gradient

Image gradient is one of the most important measures of change in an image. An image gradient is the directional change in the intensity or colour of an image. The information provided by the gradient is the magnitude and the direction. The magnitude denotes the rate of change of the image, while the direction of the gradient denotes the direction with
the most rapid change. It is given by:

$$\nabla f = \frac{\partial f}{\partial x} \hat{x} + \frac{\partial f}{\partial y} \hat{y}$$  \hspace{1cm} (4.8)

where $\frac{\partial f}{\partial x}$ is the gradient in $x$ direction and $\frac{\partial f}{\partial y}$ is the gradient in $y$ direction.

The gradient direction is calculated from:

$$\theta = \text{atan2}\left(\frac{\partial f}{\partial y}, \frac{\partial f}{\partial x}\right)$$  \hspace{1cm} (4.9)

Subsection 4.1.5 provides an overview of edge operators that produce the gradient of an image. If we define $A$ as the original image, there is a number of kernels in the literature to calculate the partial gradients:

**Sobel Kernels:**

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \ast A \quad \text{and} \quad G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \ast A$$  \hspace{1cm} (4.10)

**Prewitt Kernels:**

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} \ast A \quad \text{and} \quad G_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ +1 & +1 & +1 \end{bmatrix} \ast A$$  \hspace{1cm} (4.11)

**Scharr Kernels:**

$$G_x = \begin{bmatrix} +3 & +10 & +3 \\ 0 & 0 & 0 \\ -3 & -10 & -3 \end{bmatrix} \ast A \quad \text{and} \quad G_y = \begin{bmatrix} +3 & 0 & -3 \\ +10 & 0 & -10 \\ +3 & 0 & -3 \end{bmatrix} \ast A$$  \hspace{1cm} (4.12)
Roberts Kernels:

\[
G_x = \begin{bmatrix} +1 & \ 0 \\ 0 & -1 \end{bmatrix} * A \quad \text{and} \quad G_y = \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix} * A \quad (4.13)
\]

The most used way to calculate the gradient magnitude by use of the kernels above is:

\[
G = \sqrt{G_x^2 + G_y^2} \quad (4.14)
\]

And the gradient direction:

\[
\Theta = \text{atan2} \left( G_y, G_x \right) \quad (4.15)
\]

Sobel suggested that the mathematically correct way is to divide \( G \) by 4, although a loss of low order significant bits can occur (Sobel, 1990):

\[
G = \frac{|G_x| + |G_y|}{4} \quad (4.16)
\]

### 4.3.2 Investigation of aluminium surface features

In this section an investigation of three categories of defects and comparisons with non defective aluminium surfaces will be made. Four example surfaces that represent each class have been selected from the sample set to evaluate the features. As shown in Fig 4.17, (a) represents a surface without any defects, (b) contains a blister, (c) shows a scratch made due to handling error and (d) shows two die lines. The images are in 8bit gray-level scale, with values from 0 to 255. The size is 150x150 pixels and corresponds to approximately 5x5 cm.

Slight differences can occur at the size of the images as the height of the aluminium profile varied between each sample since the camera was mounted stationary. The purpose of the camera’s mounting method was deliberate in order to simulate an industrial environment where the placement of the imaging equipment is usually fixed.

The first and easiest information that can be extracted from an image are the first order
histogram statistics which include range, mean, min, max, standard deviation. In the following Table 4.1, a computation of the Figure’s first order statistics is made in three stages. The first group of rows shows the original images’ statistics, the second shows the statistics obtained by smoothing the images with a low-pass filter to remove noise and the third shows the statistics of the image gradients after converting the results of the gradient calculation to integer value. The gradient is calculated using Equation 4.16.

As observed by the Table 4.1, Blister type defects have higher Max values. This is due to the nature of the defect. Blisters are bubbles on the surface of the aluminium of a certain height. Their surface curvature resembles that of a sphere, thus gray-level values are higher on the areas where the direction of the camera is perpendicular to the direction of the illumination. Scratch type defects have lower Min values, to light rays that are weakened as some are redirected in other angles. The nature of the defect suggests that, since material is removed, the surface of the scratch rests lower than the rest of the aluminium surface, while
Table 4.1: Gray value measures of images in Fig 4.17

<table>
<thead>
<tr>
<th>Gray Value Measures</th>
<th>Good Surface</th>
<th>Blister</th>
<th>Scratch</th>
<th>Die Lines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>105</td>
<td>83</td>
<td>95</td>
<td>96</td>
</tr>
<tr>
<td>Max</td>
<td>169</td>
<td>252</td>
<td>170</td>
<td>187</td>
</tr>
<tr>
<td>Range</td>
<td>64</td>
<td>169</td>
<td>75</td>
<td>91</td>
</tr>
<tr>
<td>Mean</td>
<td>133.712</td>
<td>130.217</td>
<td>129.614</td>
<td>140.049</td>
</tr>
<tr>
<td>Deviation</td>
<td>13.8021</td>
<td>26.8977</td>
<td>12.2405</td>
<td>19.5581</td>
</tr>
<tr>
<td>MinS</td>
<td>108</td>
<td>91</td>
<td>99</td>
<td>106</td>
</tr>
<tr>
<td>MaxS</td>
<td>162</td>
<td>226</td>
<td>163</td>
<td>181</td>
</tr>
<tr>
<td>RangeS</td>
<td>54</td>
<td>135</td>
<td>64</td>
<td>75</td>
</tr>
<tr>
<td>MeanS</td>
<td>133.704</td>
<td>130.177</td>
<td>129.624</td>
<td>140.057</td>
</tr>
<tr>
<td>MinG</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>MaxG</td>
<td>13</td>
<td>40</td>
<td>19</td>
<td>25</td>
</tr>
<tr>
<td>RangeG</td>
<td>13</td>
<td>40</td>
<td>19</td>
<td>25</td>
</tr>
<tr>
<td>MeanG</td>
<td>3.04009</td>
<td>4.28578</td>
<td>3.01956</td>
<td>4.65933</td>
</tr>
<tr>
<td>DeviationG</td>
<td>1.96045</td>
<td>4.125</td>
<td>2.39955</td>
<td>4.08449</td>
</tr>
</tbody>
</table>

also forming a U shaped ridge in which some of the illumination rays are reflected to other directions. The Range of gray-level values in defective surfaces is greater than the non defective, since the presence of a defect greatly affects the homogeneity of gray values in the image. Die-Lines are formed usually by excess friction with the die producing a surface which appears darker than the rest, explaining the Range values being higher. The standard deviation is lowest in non defective surfaces, while having higher values on the appearance of defects, which means a higher spread of gray-level values due to the inhomogeneity of the surface. The first order statistics of the gradient also represent the inhomogeneity of the surface, having higher range and standard deviation in the presence of a defect.

Since definite conclusions cannot be drawn from a sample of each class, a selection of 6 random samples of each class was performed. Figure 4.18 shows 6 non defective sample images with the first order statistics in Table 4.2. The Min and Max gray values are very dependant on illumination and since the profile height is not constant, those values contain no significant discriminating power. Range is tied partly to the illumination and partly to the surface’s characteristics. Since Mean and Standard Deviation derive from those values, they cannot be used to offer any useful observations between different classes.
Contrary to the gray value statistics, those that derive from the image gradient are more immune to illumination. As observed the Max Values of non defective are lower than any of the three defective image groups (Tables 4.3, 4.4, 4.5). This is a result of non defective having no pronounced edges (abrupt changes in intensity). In the case of blisters the Max values are considerably higher, due to the height of the defect which results in higher gray values that provide a higher value of local gradient. Range is lowest in non defective, while
Table 4.2: Gray value measures of images in Fig 4.18

<table>
<thead>
<tr>
<th>Gray Value Measures</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Image</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>64.0</td>
<td>78.0</td>
<td>94.0</td>
<td>48.0</td>
<td>85.0</td>
<td>57.0</td>
</tr>
<tr>
<td>Max</td>
<td>80.0</td>
<td>118.0</td>
<td>160.0</td>
<td>80.0</td>
<td>152.0</td>
<td>85.0</td>
</tr>
<tr>
<td>Range</td>
<td>16.0</td>
<td>40.0</td>
<td>66.0</td>
<td>32.0</td>
<td>67.0</td>
<td>28.0</td>
</tr>
<tr>
<td>Mean</td>
<td>72.0036</td>
<td>96.6446</td>
<td>123.264</td>
<td>59.902</td>
<td>118.098</td>
<td>68.8277</td>
</tr>
<tr>
<td>Deviation</td>
<td>2.01816</td>
<td>6.96861</td>
<td>12.4003</td>
<td>4.13754</td>
<td>12.6782</td>
<td>4.18567</td>
</tr>
<tr>
<td>Smoothened Image</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MinS</td>
<td>67.0</td>
<td>80.0</td>
<td>99.0</td>
<td>52.0</td>
<td>94.0</td>
<td>59.0</td>
</tr>
<tr>
<td>MaxS</td>
<td>78.0</td>
<td>116.0</td>
<td>151.0</td>
<td>75.0</td>
<td>147.0</td>
<td>82.0</td>
</tr>
<tr>
<td>RangeS</td>
<td>11.0</td>
<td>36.0</td>
<td>52.0</td>
<td>23.0</td>
<td>53.0</td>
<td>23.0</td>
</tr>
<tr>
<td>MeanS</td>
<td>72.0029</td>
<td>96.6445</td>
<td>123.245</td>
<td>59.8829</td>
<td>118.084</td>
<td>68.8282</td>
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<td>DeviationS</td>
<td>1.57189</td>
<td>6.70501</td>
<td>12.0775</td>
<td>3.52153</td>
<td>12.3392</td>
<td>3.85737</td>
</tr>
<tr>
<td>Image Gradient</td>
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</tr>
<tr>
<td>MinG</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>MaxG</td>
<td>6.0</td>
<td>8.0</td>
<td>13.0</td>
<td>10.0</td>
<td>14.0</td>
<td>8.0</td>
</tr>
<tr>
<td>RangeG</td>
<td>6.0</td>
<td>8.0</td>
<td>13.0</td>
<td>10.0</td>
<td>14.0</td>
<td>8.0</td>
</tr>
<tr>
<td>MeanG</td>
<td>1.39507</td>
<td>1.99071</td>
<td>2.93387</td>
<td>2.13933</td>
<td>3.3572</td>
<td>1.69951</td>
</tr>
<tr>
<td>DeviationG</td>
<td>1.02027</td>
<td>1.27483</td>
<td>1.86313</td>
<td>1.44908</td>
<td>2.17462</td>
<td>1.3838</td>
</tr>
</tbody>
</table>

being highest in blisters. The same reason that applies to Max values applies to Range as well. Scratch defects have the second highest Range values followed by die Lines. The Mean values are lowest in non defective and highest in blisters. An interesting observation is to be made in the case of scratches and die lines, where range and mean are inversely proportional. This can be attributed to the size of the defect. Die lines are traverse to the length of the profile in the direction of the extrusion process, while scratches have more random orientations and not necessarily cover the same area.
Figure 4.19: Example images of blister defect
### Table 4.3: Gray value measures of images in Fig 4.19

<table>
<thead>
<tr>
<th>Gray Value Measures</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original Image</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>46.0</td>
<td>75.0</td>
<td>46.0</td>
<td>76.0</td>
<td>49.0</td>
<td>62.0</td>
</tr>
<tr>
<td>Max</td>
<td>255.0</td>
<td>200.0</td>
<td>173.0</td>
<td>255.0</td>
<td>135.0</td>
<td>146.0</td>
</tr>
<tr>
<td>Range</td>
<td>209.0</td>
<td>125.0</td>
<td>127.0</td>
<td>179.0</td>
<td>86.0</td>
<td>84.0</td>
</tr>
<tr>
<td>Mean</td>
<td>117.118</td>
<td>121.871</td>
<td>81.2591</td>
<td>130.127</td>
<td>74.0603</td>
<td>96.8472</td>
</tr>
<tr>
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<tr>
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<tr>
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<td>0.0</td>
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<td>9.74631</td>
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<td>5.66184</td>
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### Table 4.4: Gray value measures of images in Fig 4.20

<table>
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<tr>
<th>Gray Value Measures</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
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<tbody>
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<td>57.0</td>
<td>64.0</td>
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<td>Mean</td>
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<td>8.18838</td>
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<td>4.5325</td>
<td>5.92057</td>
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<tr>
<td>MinS</td>
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<td>65.0</td>
<td>71.0</td>
<td>56.0</td>
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<tr>
<td>MaxS</td>
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<td>0.0</td>
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<td>0.0</td>
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<td>2.88156</td>
<td>2.12482</td>
<td>2.00949</td>
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</table>
Figure 4.20: Example images of scratch defect
Figure 4.21: Example images of die-line defect
### Table 4.5: Gray value measures of images in Fig 4.21

<table>
<thead>
<tr>
<th>Gray Value Measures</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original Image</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>Min</td>
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<td>61.0</td>
<td>77.0</td>
<td>58.0</td>
<td>62.0</td>
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<tr>
<td>Max</td>
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<td>109.0</td>
<td>145.0</td>
<td>103.0</td>
<td>154.0</td>
<td>100.0</td>
</tr>
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<td>Range</td>
<td>32.0</td>
<td>48.0</td>
<td>68.0</td>
<td>45.0</td>
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<tr>
<td>Mean</td>
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<td>78.1749</td>
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<td>75.052</td>
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<td>8.81133</td>
<td>11.7154</td>
<td>8.44907</td>
<td>17.5633</td>
<td>9.08584</td>
</tr>
<tr>
<td><strong>Smoothed Image</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MinS</td>
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<td>60.0</td>
<td>69.0</td>
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<tr>
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<td>141.0</td>
<td>100.0</td>
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<td>93.0</td>
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<tr>
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<td>75.0448</td>
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<td>17.2019</td>
<td>8.22986</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>MinG</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>MaxG</td>
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<td>10.0</td>
<td>23.0</td>
<td>16.0</td>
<td>26.0</td>
<td>22.0</td>
</tr>
<tr>
<td>RangeG</td>
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<td>10.0</td>
<td>23.0</td>
<td>16.0</td>
<td>26.0</td>
<td>22.0</td>
</tr>
<tr>
<td>MeanG</td>
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<td>2.32836</td>
<td>3.24044</td>
<td>2.8668</td>
<td>4.31831</td>
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<td>1.68407</td>
<td>2.9776</td>
<td>2.14482</td>
<td>3.26186</td>
<td>3.51828</td>
</tr>
</tbody>
</table>

Concluding certain observations can be made. Looking at values from original images (and smoothed images):

- Min - Max values depend greatly on illumination (often as a consequence of profile height) and / or the presence of a defect.

- Range values are usually higher in the presence of a defect.

- Mean values depend more on illumination than defects.

- Standard deviation values depend on the nature of the defect.

For values obtained from image gradients:

- Min values are all 0, due to the homogeneous texture presence in all of the samples.

- Max values depend on the severity of the defect, while being lowest in non defective samples.

- Range values are essentially the same as Max values, since Min value is a constant 0 across all samples.
• Mean values are lowest in non defective, while highest where the defect is more intense.

• Standard deviation values depend on the size of the defective area of a sample.

4.4 Feature extraction

4.4.1 Co-occurrence matrix features

Co-occurrence matrices are a commonly applied statistical approach for texture features extraction that takes into account relative distances and orientation of pixels with co-occurring values (Haralick et al., 1973; Haralick, 1979; Georgieva and Jordanov, 2009; Davies, 2012). A co-occurrence matrix or co-occurrence distribution is a matrix or distribution that is defined over an image to be the distribution of co-occurring values at a given offset and direction. Mathematically, a co-occurrence matrix $C$ is defined over an $n \times m$ image $I$, parametrized by an offset $(\Delta x, \Delta y)$, as:

$$C(\Delta x, \Delta y)(i, j) = \sum_{p,q=1}^{N,M} \begin{cases} 1 & \text{if } I(p, q) = i \text{ and } I(p + \Delta x, q + \Delta y) = j \\ 0 & \text{otherwise} \end{cases} \quad (4.17)$$

where $i$ and $j$ are the image intensity values, $p$ and $q$ are the spatial positions in the image $I$ and the offset $(\Delta x, \Delta y)$ depends on the direction $\theta$ used and the distance $d$ at which the matrix is computed. The value of the image is originally referred to the gray-scale value of the specified pixel, but could be anything, from a binary 0/1 value to 32bit color and beyond.

Properties are derived from co-occurrence matrices, amongst those are Contrast, Homogeneity, Energy and Correlation. The first property, Contrast, measures the intensity contrast between neighboring pixels. Homogeneity measures the closeness of the distribution of elements in the co-occurrence matrix to its diagonal. Energy calculates the
sum of squared elements in the co-occurrence matrix and \textit{Correlation} measures the linear dependency of grey levels on neighboring pixels.

\begin{align*}
\text{Contrast} &= \sum_{i,j} (i - j)^2 C_{i,j} \quad (4.18) \\
\text{Homogeneity} &= \sum_{i,j} \frac{C_{i,j}}{1 + (i - j)^2} \quad (4.19) \\
\text{Energy} &= \sum_{i,j} C_{i,j}^2 \quad (4.20) \\
\text{Correlation} &= \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j) C_{i,j}}{\sigma_i \sigma_j} \quad (4.21)
\end{align*}

where:

\begin{align*}
\mu_i &= \sum_{i,j} i \times C_{i,j} \quad (4.22) \\
\mu_j &= \sum_{i,j} j \times C_{i,j} \quad (4.23) \\
\sigma_i &= \sqrt{\sum_{i,j} (i - \mu_i)^2 C_{i,j}} \quad (4.24) \\
\sigma_j &= \sqrt{\sum_{i,j} (j - \mu_j)^2 C_{i,j}} \quad (4.25)
\end{align*}

A calculation of co-occurrence matrices was performed for the initial 4 example pictures (Figure 4.17) which is shown in Figure 4.22. The distance used was 1 (neighbouring pixel) and the directions $\theta = 0^0$ and $\theta = 90^0$. To conform with the literature (Clausi, 2002), the co-occurrence matrices were scaled to 6bit (64 gray levels) to avoid unnecessary computational load. The four common features were calculated in Table 4.6.
Figure 4.22: Co-occurrence matrices of Figure 4.17
Table 4.6: Co-occurrence matrix features for images of Figure 4.17

<table>
<thead>
<tr>
<th>Features</th>
<th>Non Defective</th>
<th>Blister</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>$\theta = 0^0$</td>
<td>$\theta = 90^0$</td>
</tr>
<tr>
<td>Direction</td>
<td>0.0637362</td>
<td>0.0451872</td>
</tr>
<tr>
<td>Energy</td>
<td>0.992788</td>
<td>0.984707</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.917002</td>
<td>0.8303</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.165996</td>
<td>0.349172</td>
</tr>
<tr>
<td>Scratch</td>
<td>0.0720302</td>
<td>0.0543623</td>
</tr>
<tr>
<td>Energy</td>
<td>0.990535</td>
<td>0.982055</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.918474</td>
<td>0.845132</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.172931</td>
<td>0.32434</td>
</tr>
<tr>
<td>Die Line</td>
<td>0.165996</td>
<td>0.349172</td>
</tr>
</tbody>
</table>

Energy measures textural uniformity. It can have values between 0 and 1, with higher values representing a more uniform texture, when the gray level distribution has either a constant or periodic form. For both orientations, non defective and scratch have more homogeneous texture. This property not only depends on the presence of a defect, but also on the texture roughness. Correlation is expressed by the correlation coefficient between two gray values $i$ and $j$ and is a measure of gray level linear dependencies in the image. High Correlation values imply a linear relationship between pixel pairs. As observed by the four samples, Correlation is higher for horizontal pixel pairs and lower for vertical. This is directly tied to the direction of the extrusion. Correlation is also uncorrelated to Energy or Contrast. Homogeneity measures texture homogeneity and receives higher values for smaller differences in gray values of pixel pairs. Blister and Die line defects exhibit lower Homogeneity along the $90^0$ direction which corresponds to the impact the defect has on the value difference of pixel pairs perpendicular to the direction of extrusion. Contrast represents the concentration along the GLCM’s main diagonal. A low Contrast value is attributed to low contrast of image texture. The absence of a defect, or the low area of a scratch are not adequate to increase the contrast values in the $90^0$ direction, as opposed to the blister and die line which have a high impact on the image’s vertical contrast.
### Table 4.7: Co-occurrence matrix features for images of Figure 4.18

<table>
<thead>
<tr>
<th>Features</th>
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<th>d</th>
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<th>f</th>
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</thead>
<tbody>
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<td>Correlation</td>
<td>0.833383</td>
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<td>0.960296</td>
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<td>0.921946</td>
<td>0.950246</td>
<td>0.927315</td>
<td>0.959888</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.0940492</td>
<td>0.149217</td>
<td>0.156107</td>
<td>0.0995078</td>
<td>0.145369</td>
<td>0.0802237</td>
</tr>
</tbody>
</table>

\[ \theta = 0^0 \]

| Energy   | 0.347356  | 0.112507  | 0.0481024 | 0.241669  | 0.0411987 | 0.219805  |
| Correlation | 0.667255 | 0.967234  | 0.981263  | 0.850324  | 0.978703  | 0.903238  |
| Homogeneity | 0.905996 | 0.906331  | 0.832864  | 0.875132  | 0.807982  | 0.902309  |
| Contrast | 0.188009  | 0.187338  | 0.340716  | 0.249843  | 0.139597  | 0.195705  |

\[ \theta = 90^q \]

| Energy   | 0.0589556 | 0.0550818 | 0.0915218 | 0.0558398 | 0.119542  | 0.107329  |
| Correlation | 0.99825  | 0.996193  | 0.993265  | 0.996263  | 0.987248  | 0.983673  |
| Homogeneity | 0.885255 | 0.911548  | 0.924     | 0.902617  | 0.936577  | 0.930201  |
| Contrast | 0.339597  | 0.179374  | 0.152215  | 0.204966  | 0.126846  | 0.139597  |

### Table 4.8: Co-occurrence matrix features for images of Figure 4.19

<table>
<thead>
<tr>
<th>Features</th>
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<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
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</thead>
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<tr>
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<td>0.0550818</td>
<td>0.0915218</td>
<td>0.0558398</td>
<td>0.119542</td>
<td>0.107329</td>
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<tr>
<td>Correlation</td>
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<td>0.993265</td>
<td>0.996263</td>
<td>0.987248</td>
<td>0.983673</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.885255</td>
<td>0.911548</td>
<td>0.924</td>
<td>0.902617</td>
<td>0.936577</td>
<td>0.930201</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.339597</td>
<td>0.179374</td>
<td>0.152215</td>
<td>0.204966</td>
<td>0.126846</td>
<td>0.139597</td>
</tr>
</tbody>
</table>

\[ \theta = 0^0 \]

| Energy   | 0.0373307 | 0.0370175 | 0.0614587 | 0.0388614 | 0.081752  | 0.0651736 |
| Correlation | 0.991795 | 0.987957  | 0.980788  | 0.984299  | 0.962751  | 0.948918  |
| Homogeneity | 0.739565 | 0.801599  | 0.809709  | 0.782412  | 0.831803  | 0.799678  |
| Contrast | 1.59888  | 0.480403  | 0.433736  | 0.854765  | 0.367427  | 0.431141  |

\[ \theta = 90^q \]
### Table 4.9: Co-occurrence matrix features for images of Figure 4.20

<table>
<thead>
<tr>
<th>Features</th>
<th>a</th>
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<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
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<td>0.978124</td>
<td>0.975107</td>
<td>0.939876</td>
<td>0.968867</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.918953</td>
<td>0.886435</td>
<td>0.926443</td>
<td>0.926474</td>
<td>0.937119</td>
<td>0.940054</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.209128</td>
<td>0.535168</td>
<td>0.165906</td>
<td>0.163266</td>
<td>0.135749</td>
<td>0.121611</td>
</tr>
<tr>
<td>θ = 90°</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Energy</td>
<td>0.0804947</td>
<td>0.0544413</td>
<td>0.0902976</td>
<td>0.0814363</td>
<td>0.176537</td>
<td>0.127769</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.93331</td>
<td>0.984846</td>
<td>0.955531</td>
<td>0.933718</td>
<td>0.904882</td>
<td>0.928861</td>
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<tr>
<td>Homogeneity</td>
<td>0.802779</td>
<td>0.844013</td>
<td>0.83757</td>
<td>0.80583</td>
<td>0.893396</td>
<td>0.86579</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.408188</td>
<td>0.316913</td>
<td>0.336242</td>
<td>0.428501</td>
<td>0.214497</td>
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### Table 4.10: Co-occurrence matrix features for images of Figure 4.21

<table>
<thead>
<tr>
<th>Features</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>θ = 0°</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.2195</td>
<td>0.114797</td>
<td>0.0800609</td>
<td>0.120772</td>
<td>0.0566081</td>
<td>0.115534</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.957664</td>
<td>0.989977</td>
<td>0.992266</td>
<td>0.987274</td>
<td>0.99579</td>
<td>0.987202</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.950917</td>
<td>0.952595</td>
<td>0.937114</td>
<td>0.947114</td>
<td>0.921955</td>
<td>0.944774</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.0981655</td>
<td>0.0948098</td>
<td>0.125772</td>
<td>0.105772</td>
<td>0.156197</td>
<td>0.110559</td>
</tr>
<tr>
<td>θ = 90°</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.15699</td>
<td>0.0834662</td>
<td>0.0564807</td>
<td>0.0779731</td>
<td>0.0338321</td>
<td>0.0540668</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.873329</td>
<td>0.971027</td>
<td>0.970798</td>
<td>0.955732</td>
<td>0.983357</td>
<td>0.914827</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.861163</td>
<td>0.863615</td>
<td>0.814013</td>
<td>0.831043</td>
<td>0.753924</td>
<td>0.72132</td>
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<tr>
<td>Contrast</td>
<td>0.287338</td>
<td>0.273736</td>
<td>0.47302</td>
<td>0.361432</td>
<td>0.615749</td>
<td>0.736689</td>
</tr>
</tbody>
</table>
4.4.2 GLCM results discussion

From the Tables 4.7, 4.8, 4.9 and 4.10 there are some important observations to be made:

- Blisters show difference in values for both directions ($\theta = 0^\circ$ and $\theta = 90^\circ$) compared to the non defective samples. Usually Correlation and Contrast are higher, while Homogeneity is lower.

- Scratches are usually more subtle in the $90^\circ$ direction but their values deviate from non defective samples in the $0^\circ$ direction, where Homogeneity is lower and Contrast is higher.

- Die lines are analogous to Scratches but for the $0^\circ$ direction, where Energy and Homogeneity are lower, while Contrast is higher.

- Comparing GLCM texture measure values between defects is greatly dependant on the size of the defect and the image’s illumination.

4.4.3 Gray level gradient co-occurrence matrices

Gray level gradient co-occurrence matrices are less common in the literature. They take into account the relationship between a pair of $i, j$, where $i$ belongs to the original image and $j$ belongs to its gradient. The element $h_{i,j}$ of GLGCM is defined as the probability of a pixel number which has gray value $i$ in the normalized gray image $F_{m,n}$ and gradient value $j$ in the normalized gradient image $G_{m,n}$.

Image normalization is achieved with:

$$F_{m,n} = INT\left[\frac{f_{m,n} \times N_g}{f_{max}}\right] + 1 \quad (4.26)$$

Where $f_{m,n}$ is the gray value, $f_{max}$ the maximum gray value, $N_g$ the normalized maximum gray value.
Gradient normalization is achieved with:

\[ G_{m,n} = \text{INT} \left[ \frac{g_{m,n} \times N_s}{g_{\text{max}}} \right] + 1 \quad (4.27) \]

Where \( g_{m,n} \) is the gradient value, \( g_{\text{max}} \) the maximum gradient value, \( N_s \) the normalized maximum gradient value.

Then count the number of pixels which satisfy \( F_{m,n} = i \) and \( G_{m,n} = j \), for displacement \( d \) and direction \( \theta \), to get \( H_{ij} \). The gray level gradient co-occurrence matrix is given by:

\[ H = \sum_{i,j}^{N_g,N_s} H_{ij} \quad (4.28) \]

The normalized GLGCM is given by:

\[ \hat{H}_{ij} = \frac{H_{ij}}{(N_g \times N_s)} \quad (4.29) \]

Features obtained from GLGCM are similar to those of GLCM. Therefore we have:

\[ \text{Contrast} = \sum_{i,j}^{N_g,N_s} (i - j)^2 \hat{H}_{i,j} \quad (4.30) \]

\[ \text{Homogeneity} = \sum_{i,j}^{N_g,N_s} \frac{\hat{H}_{i,j}}{1 + (i - j)^2} \quad (4.31) \]

\[ \text{Energy} = \sum_{i,j}^{N_g,N_s} \hat{H}_{i,j}^2 \quad (4.32) \]

\[ \text{Correlation} = \sum_{i,j}^{N_g,N_s} \frac{(i - \mu_i)(j - \mu_j)\hat{H}_{i,j}}{\sigma_i \sigma_j} \quad (4.33) \]

where:

\[ \mu_i = \sum_{i,j}^{N,N_M} i \times \hat{H}_{i,j} \quad (4.34) \]
\[ \mu_j = \sum_{i,j} j \times \hat{H}_{i,j} \]  
\[ \sigma_i = \sqrt{\sum_{i,j} (i - \mu_i)^2 \hat{H}_{i,j}} \]  
\[ \sigma_j = \sqrt{\sum_{i,j} (j - \mu_j)^2 \hat{H}_{i,j}} \]

### 4.5 Novel feature extraction

#### 4.5.1 Gradient Only Co-occurrence Matrices

Gradient only co-occurrence matrices is a novel technique that differs from the GLCM and GLGCM approaches encountered so far in the literature. While GLCM is calculated from the original image and GLGCM is calculated using a pair of \( i, j \), where \( i \) is a value of the original image and \( j \) is a value from the gradient, gradient only co-occurrence matrices (GOCM) are calculated only from the image gradient after it has been transformed to integer. This technique was developed during investigation of appropriate feature extraction methods of textural information for the task of classifying extruded aluminium surface images. The following equation 4.36 shows the integer conversion process for the gradient calculation.

\[ G_{INT} = \text{int}[G] = \text{INT} \left[ \frac{|G_x| + |G_y|}{4} \right] \cup A = \{0, 1, 2, 3 \ldots \} \in \mathbb{Z} \]  
\[ \binom{n}{k} = \frac{n!}{k!(n-k)!} \]  

Table 4.11 shows the resulting co-occurrence matrix and the Sobel calculations respectively for the same part of a blister defect image. The co-occurrence matrices are impractical when the numbers are Real \( \mathbb{R} \), while having decimal digits. There are too
many combinations of numbers that the possibility of one being next to another one is very low. From equation 4.37 it is possible to calculate the difference in combinations using real ($\mathbb{R}$) and integer ($\mathbb{Z}$) values. Assuming the co-occurrence matrix will have $N = 64$, for integers $n = 64$ and $k = 2$ (since the co-occurrence matrix shows the possibility 2 numbers are at a distance $d$ from each other in a certain direction $\theta$), while for reals $n = 64 \times 10^x$ where $x$ is the number of decimal digits and $k = 2$. Integer numbers will have 2016 possible combinations while real numbers with 3 decimal digits will have $2.047968 \times e^9$ possible combinations. In the first table of 4.11 the possibilities of pixel pair are all 0, with the exception that 0 is next to 0 which occurs 4 times, while in the second the co-occurrence matrix appears normal with high frequency of pixel pairs along its main diagonal.

Table 4.11: The difference in co-occurrence matrix calculation with Sobel and integer transformed
Sobel taken from a part of the same image of a blister defect

<table>
<thead>
<tr>
<th>Co-oc matrix from image gradient with $\mathbb{R}$</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Co-oc matrix from image gradient with $\mathbb{Z}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>10406  1414  1  0  0  0  0  0  0</td>
</tr>
<tr>
<td>1404  5937  452  3  0  0  0  0  0</td>
</tr>
<tr>
<td>3  448  1176  106  3  0  0  0  0</td>
</tr>
<tr>
<td>0  0  108  292  31  1  0  0  0</td>
</tr>
<tr>
<td>0  1  2  30  98  31  0  0  0</td>
</tr>
<tr>
<td>0  0  0  34  129  23  0  0  0</td>
</tr>
<tr>
<td>0  0  0  0  25  60  11 0 0</td>
</tr>
</tbody>
</table>
Figure 4.23: Co-occurrence matrices of Figure 4.17 after gradient calculation and integer transformation
As observed in the visual representation of GOCM (Figure 4.23) there is a higher occurrence of pixel pairs closer to the starting pair \((i, j) = (0, 0)\) at the top left corner of the co-occurrence matrix. An image gradient shows the change in intensity values of an image, thus homogeneous segments of the image are closer to 0, which translates in a plethora of \((i, j) = (0, 0)\) pixel pair occurrences. Higher numbers along and away from the GOCM main diagonal represent more intense changes. One question that arises from Figure 4.23 is; What is the scaling used in GOCM? The scaling remains 6bit (64 gray values) even if it seems unnecessary. The reason is when there is a sharp edge in an image, where the gradient magnitude value is high (for the sample set the max image gradient value was 125), still needs to be room to accommodate those values, because using 32 or 16 gray values the accuracy would be reduced in the presence of a higher range of values. From the Tables 4.13, 4.14, 4.15 and 4.16 comparisons between the statistical texture values will follow. T-tests were also conducted for verifying the statistical significance of using values of \(\theta = 0^0\) and \(\theta = 90^0\) with results in the the following table 4.12 (where \(h = 1\) means the null hypothesis was rejected).

<table>
<thead>
<tr>
<th>Feature pairs</th>
<th>h</th>
<th>p</th>
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</thead>
<tbody>
<tr>
<td>Contrast-Contrast90</td>
<td>1</td>
<td>5.8772e-30</td>
</tr>
<tr>
<td>Correlation-Correlation90</td>
<td>1</td>
<td>4.7693e-62</td>
</tr>
<tr>
<td>Energy-Energy90</td>
<td>1</td>
<td>1.7989e-83</td>
</tr>
<tr>
<td>Homogeneity-Homogeneity90</td>
<td>1</td>
<td>1.3003e-62</td>
</tr>
</tbody>
</table>

4.5.2 GOCM results discussion

A high Energy feature value for GOCM is attributed to a concentration of fewer elements in the co-occurrence matrix. This means more pixel pairs with 0 probability, while few have very large numbers. Energy values of GOCM are much higher than their GLCM counterparts, because gradient magnitude images are more homogeneous compared to intensity images. In the presence of a defect, Energy receives lower values, depending on
the size and severity of the defect. A blister that covers a higher surface area while protruding more will receive considerably lower Energy values than homogeneous surfaces. Looking at defective sample (a) of Figure 4.19, it appears bigger in size and higher in height from the rest. Comparing the Energy values, it apparent that it has significantly lower Energy in both directions. Energy at $\theta = 90^0$ is particularly useful in determining the severity of die lines. In Figure 4.21, (e) and (f) appear more intense than the rest, which is verified by their low Energy values 0.178 and 0.162 respectively.

High Correlation feature values are attributed to the presence of linear structure along the specified direction ($\theta$), therefore Correlation values will be higher in the presence of a defect as it introduces structure in the image. In the case of image gradient this structure are the edges of the defect. The very nature of the process will affect the Correlation values. The presence of linear structure in all of the aluminium profiles, due to the friction developed during extrusion, results in the visual appearance of a surface has a directional texture along the extrusion direction. This is a linear structure which explains the higher Correlation values observed along $\theta = 0^0$ as opposed to $\theta = 90^0$. Die lines will have significantly higher Correlation values along the $\theta = 0^0$ direction than $\theta = 90^0$, as the edges appear parallel to the extrusion’s direction.

Homogeneity values don’t show a great variation. Especially along the direction of extrusion ($\theta = 0^0$), Homogeneity is similar. Only on blisters and scratches where there is variation perpendicular to extrusion’s direction, Homogeneity obtains a lower value, due to inhomogeneous distribution of gray values. Since Homogeneity assumes higher values for smaller pixel pair differences, only strong edges are capable of reducing its value, so images with a more prominent defect will have lower values.

Contrast, being the statistical measure that represents the amount of local variations present in an image, will receive higher values in the presence of strong gray level intensity transitions. A gradient magnitude image with strong edges will receive higher Contrast values. For non defective images, Contrast will be higher perpendicular to the extrusion direction as there is a stronger possibility of a intensity change. Die lines show significantly
higher *Contrast* values for $\theta = 90^0$, while the more prominent the defect the greater the value. Their *Contrast* values for $\theta = 0^0$ are similar to non defective as there are no significant intensity changes. Scratches have higher *Contrast* for both directions, while Blisters show greater difference along the $\theta = 90^0$ direction.

**Table 4.13:** Co-occurrence matrix features for image gradients (integer) of Figure 4.18

<table>
<thead>
<tr>
<th>Features</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta = 0^0$</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.911454</td>
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<td>0.408602</td>
<td>0.645258</td>
<td>0.354992</td>
<td>0.780042</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.59862</td>
<td>0.45423</td>
<td>0.676414</td>
<td>0.700265</td>
<td>0.757468</td>
<td>0.799426</td>
</tr>
<tr>
<td>Homogeneity</td>
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<td>0.914295</td>
<td>0.957405</td>
<td>0.914586</td>
<td>0.981051</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.0255481</td>
<td>0.117539</td>
<td>0.171409</td>
<td>0.0851902</td>
<td>0.170828</td>
<td>0.0378971</td>
</tr>
</tbody>
</table>

| $\theta = 90^0$ |       |       |       |       |       |       |
| Energy     | 0.892098 | 0.658503 | 0.316913 | 0.555029 | 0.247798 | 0.708649 |
| Correlation| 0.276937 | 0.309885 | 0.270354 | 0.251668 | 0.296486 | 0.353074 |
| Homogeneity| 0.976913 | 0.925624 | 0.817338 | 0.893955 | 0.780515 | 0.938676 |
| Contrast   | 0.0461745 | 0.148859 | 0.387338 | 0.213378 | 0.496421 | 0.122864 |

**Table 4.14:** Co-occurrence matrix features for image gradients (integer) of Figure 4.19

<table>
<thead>
<tr>
<th>Features</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta = 0^0$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.264805</td>
<td>0.330297</td>
<td>0.368634</td>
<td>0.29336</td>
<td>0.453929</td>
<td>0.358579</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.972871</td>
<td>0.857861</td>
<td>0.877607</td>
<td>0.947428</td>
<td>0.862966</td>
<td>0.811073</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.882485</td>
<td>0.901629</td>
<td>0.926559</td>
<td>0.8934</td>
<td>0.939978</td>
<td>0.920814</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.325235</td>
<td>0.199642</td>
<td>0.147204</td>
<td>0.218568</td>
<td>0.120045</td>
<td>0.158479</td>
</tr>
</tbody>
</table>

| $\theta = 90^0$ |       |       |       |       |       |       |
| Energy     | 0.18767 | 0.245236 | 0.276176 | 0.217125 | 0.35663 | 0.245368 |
| Correlation| 0.892644 | 0.613853 | 0.676822 | 0.804728 | 0.611592 | 0.423585 |
| Homogeneity| 0.754577 | 0.784458 | 0.820541 | 0.766255 | 0.843132 | 0.77685 |
| Contrast   | 1.28971 | 0.542237 | 0.38877 | 0.811633 | 0.340582 | 0.483669 |
### Table 4.15: Co-occurrence matrix features for image gradients (integer) of Figure 4.20

<table>
<thead>
<tr>
<th>Features</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>θ = 0°</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.345979</td>
<td>0.373777</td>
<td>0.431398</td>
<td>0.380094</td>
<td>0.645855</td>
<td>0.538171</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.764222</td>
<td>0.773985</td>
<td>0.781471</td>
<td>0.814172</td>
<td>0.741385</td>
<td>0.75953</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.90675</td>
<td>0.874057</td>
<td>0.922329</td>
<td>0.916526</td>
<td>0.945539</td>
<td>0.941593</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.244385</td>
<td>0.644072</td>
<td>0.182819</td>
<td>0.20774</td>
<td>0.137808</td>
<td>0.127338</td>
</tr>
<tr>
<td><strong>θ = 90°</strong></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.236727</td>
<td>0.310655</td>
<td>0.332789</td>
<td>0.268721</td>
<td>0.5993</td>
<td>0.452676</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.562116</td>
<td>0.878527</td>
<td>0.569604</td>
<td>0.553951</td>
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<td>0.50532</td>
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<td>Homogeneity</td>
<td>0.787884</td>
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<tr>
<td>Contrast</td>
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<td>0.162148</td>
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### Table 4.16: Co-occurrence matrix features for image gradients (integer) of Figure 4.21

<table>
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<tr>
<th>Features</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>θ = 0°</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.597985</td>
<td>0.601314</td>
<td>0.431959</td>
<td>0.454222</td>
<td>0.281962</td>
<td>0.298296</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.828432</td>
<td>0.775416</td>
<td>0.896075</td>
<td>0.822352</td>
<td>0.872024</td>
<td>0.925161</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.962783</td>
<td>0.956734</td>
<td>0.93868</td>
<td>0.940805</td>
<td>0.907517</td>
<td>0.939101</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.0745414</td>
<td>0.0865324</td>
<td>0.12264</td>
<td>0.118389</td>
<td>0.185503</td>
<td>0.122013</td>
</tr>
<tr>
<td><strong>θ = 90°</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.494606</td>
<td>0.51535</td>
<td>0.328665</td>
<td>0.339446</td>
<td>0.178004</td>
<td>0.162417</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.421264</td>
<td>0.426423</td>
<td>0.545406</td>
<td>0.419249</td>
<td>0.492696</td>
<td>0.501019</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.882094</td>
<td>0.891266</td>
<td>0.817005</td>
<td>0.825472</td>
<td>0.73536</td>
<td>0.710604</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.252349</td>
<td>0.221655</td>
<td>0.538479</td>
<td>0.388143</td>
<td>0.736376</td>
<td>0.814497</td>
</tr>
</tbody>
</table>
4.5.3 Proposed novel GOCM methodology

The steps to the novel approach presented so far are shown in Figure 4.24. First step is to acquire an image using proper hardware and illumination. Then a division of the image into sub-images is required. This step is essential in reducing the size of the textures for co-occurrence calculation. Locating defects on the workpiece is also made easier if each sub-image is assigned a handle. The sub-images are processed with a low-pass filter removing noise, then the gradient magnitude of each one is calculated. The gradient magnitude values are converted from $\mathbb{R}$ to $\mathbb{Z}$. Co-occurrence matrices are generated and the statistical features are calculated and extracted. This feature set will be the input of the classification technique.

![Diagram](image.png)

*Figure 4.24: GOCM statistical feature extraction methodology*
4.6 Classification methodology

Based on the work by McCulloch and Pitts (1943), Artificial Neural Networks quickly became a widely adopted classification tool. They are modeled after biological neural networks and perform function estimations or approximations from a large number of inputs. There are several different techniques and algorithms in the literature but for this research a feed-forward neural network (Figure 4.25) with Scaled Conjugate Gradient algorithm was used (Møller, 1993). The layers of the neural network are connected with weights which show connection strength between neurons and are represented by the weight vector:

$$ w = (..., \ w_{ij}^{(l)}, w_{i+l+j}^{(l)}, ..., w_{N_l}^{(l)}, \theta_j^{(l+1)}, w_{i+1+j}^{(l)}, w_{i+j}^{(l)}, w_{i+l+1+j}^{(l)}, ...) \ (4.40) $$

where $w_{ij}^{(l)}$ is the weight from unit number $i$ in layer $l$ to unit number $j$ in layer number $l + 1$, $N_l$ is the number of units in layer $l$, and $\theta_j^{(l+1)}$ is the bias for unit number $j$ in layer $l + 1$. For the error function $E(w)$, the MSE was selected as it is widely adopted (Bishop...
et al., 1995; Engelbrecht, 2007):

\[ E(w) = \frac{1}{2} \sum_{i=1}^{\tau} (o_i^p - t_i^p)^2 \]  \hspace{1cm} (4.41)

\[ F = \frac{1}{p} \sum_{p=1}^{p} E(w) \]  \hspace{1cm} (4.42)

where \( o^p \) is the network’s output for the pattern \( p \), \( t^p \) is the target vector and \( P \) is the number of training patterns.

For the network’s hidden and output layers’ transfer function, \( \text{Tanh} \) (Figure 4.26) was chosen as it was proven to result in faster training than \( \text{Logistic} \) (Bishop et al., 1995; Engelbrecht, 2007).

\[ y = \tanh x \]

**Figure 4.26: Hyperbolic Tangent transfer function**

### 4.6.1 Scaled Conjugate Gradient Algorithm

Møller (1993) introduced the Scaled Conjugate Gradient Algorithm (SCG) as a speed up to the standard backpropagation algorithm. The aim was to reduce user input and improve performance on large-scale problems while modifying the existing Conjugate Direction methods (Hestenes, 1978).

The algorithm by Møller (1993) is detailed below:
1. Choose weight vector $w_1$ and scalars $\sigma > 0$, $\lambda_1 > 0$ and $\bar{\lambda}_1 = 0$. Set $p_1 = r_1 = -E'(w_1), k = 1$ and $\text{success} = \text{true}$.

2. If $\text{success} = \text{true}$ then calculate second order information:

$$\sigma_k = \frac{\sigma}{|p_k|} \quad (4.43)$$

$$s_k = \frac{E'(w_k + \sigma_k p_k) - E'(w_k)}{\sigma_k} \quad (4.44)$$

$$\delta_k = p_k^T s_k \quad (4.45)$$

3. Scale $s_k$:

$$s_k = s_k + (\lambda_k - \bar{\lambda}_k)p_k \quad (4.46)$$

$$\delta_k = \delta_k + (\lambda_k - \bar{\lambda}_k)|p_k|^2 \quad (4.47)$$

4. If $\delta_k \leq 0$ then make the Hessian matrix positive definite:

$$s_k = s_k + (\lambda_k - 2\frac{\delta_k}{|p_k|^2})p_k \quad (4.48)$$

$$\bar{\lambda}_k = 2(\lambda_k - \frac{\delta_k}{|p_k|^2}) \quad (4.49)$$

$$\delta_k = -\delta_k + \lambda_k |p_k|^2, \lambda_k = \bar{\lambda}_k. \quad (4.50)$$

5. Calculate step size:

$$\mu_k = p_k^T r_k, \alpha_k = \frac{\mu_k}{\delta_k} \quad (4.51)$$
6. Calculate the comparison parameter:

$$
\Delta_k = \frac{2\delta_k [E(w_k) - E(w_k + \alpha_k p_k)]}{\mu_k^2}
$$

(4.52)

7. If $$\Delta_k \geq 0$$ then a successful reduction in error can be made

$$w_{k+1} = w_k + \alpha_k p_k$$

(4.53)

$$r_{k+1} = -E'(w_{k+1})$$

(4.54)

$$\bar{\lambda}_k = 0, \text{success} = \text{true}$$

(4.55)

a) If $$k \ mod \ N = 0$$ then restart algorithm: $$p_{k+1} = r_{k+1}$$ else create new conjugate direction:

$$\beta_k = \frac{|r_{k+1}|^2 - r_{k+1}r_k}{\mu_k}$$

(4.56)

$$p_{k+1} = r_{k+1} + \beta_k p_k$$

(4.57)

b) If $$\Delta_k \geq 0.75$$ then reduce the scale parameter: $$\lambda_k = 0.5\lambda_k$$, else a reduction in error is not possible: $$\bar{\lambda}_k = \lambda_k, \text{success} = \text{false}$$.

8. If $$\Delta_k < 0.25$$ then increase the scale parameter: $$\lambda_k = 4\lambda_k$$

9. If the steepest descent direction $$r_k \neq 0$$ then set $$k = k + 1$$ and go to 2 else terminate and return $$w_{k+1}$$ as the desired minimum.
4.7 Summary

This chapter begun with a short introduction to machine vision with the application of image processing and blob analysis techniques for surfaces of extruded aluminium profiles. Some of the techniques applied were image enhancement, smoothing, segmentation, edge extraction, and morphological operations. A description of the hardware used to obtain images from the test samples followed. Image gradient magnitude was emphasized as it is a very important step of image processing leading to the created novel methodology. A general investigation on first order statistics of a small subset of the sample was performed. Statistical features of co-occurrence matrices were calculated for the same samples and discussed. The novel methodology created and described in this chapter was based on the image gradient magnitude and GLCM. The same sample set was used for measurements and discussion. A step by step methodology for feature extraction was proposed along with selection of a classification methodology from the literature. Both will be applied in the next chapter for the entire sample set using two different case studies.
Chapter 5  Surface defect classification of extruded aluminium profiles

5.1 Case study: A three class problem

The sample set comprises of 145 images of 150x150 pixels in 8bit gray-scale with 8 features each, distributed in three categories: non-defective (40%); blisters (37%); and scratches (23%), with their distribution shown in Figure 5.1. The samples are surface images of industrial produced aluminum from a hot extrusion factory. MVTec Halcon version 9.0 (an industrial machine vision tool) was used to process the images and extract the feature matrix (source code in Appendix B). Matlab version 2012b was used to process the features matrix and allow different combinations of features to be used (source code in Appendix C). The dataset was normalized to minimum and maximum values -1 and 1 respectively, with the following box-and-whisker diagram representing the original feature values (Figure 5.2).

From Figure 5.2 a conclusion can be drawn that Homogeneity and Homogeneity90 are the least important features, a fact which is attributed to the low extend of the whiskers in the box-and-whisker diagram (their variance is small). If the dimensionality of the problem was to be reduced, those are the first features to consider eliminating. This can be further investigated using Principal Components Analysis and exploring how the features affect the most important principal components. The scree plot (Figure 5.3) depicts the principal components that explain 95% of the total variance.

The first principal component accounts for 75.99% of the total variance and the second component for 12.72%, to a sum total of 88.71% of the total variance. From the bi-
plot (Figure 5.4) an observation can be made that Energy, Energy90, Homogeneity, Homogeneity90 have approximately the same effect on the first 2 principal components, due to same direction, approximately same vector size and similar angles.

The assumption from the previous evidence suggests that 5 features will give enough performance for the classification. Supposedly the selection of Contrast, Contrast90, Energy, Correlation, Correlation90 will provide the same results as the full feature set of 8 features. Before moving to the classification, an investigation of whether the features are linearly separable or not was conducted, in order to select an appropriate classification technique. One of the ways to present the results is via scatter plots, in which random features from all three classes were selected to be plotted against each other (Figure 5.5). The data are non linearly separable suggesting that Multi-layer Perceptrons or Support
Figure 5.3: Scree plot of the principal components with 95% total variance

Figure 5.4: Bi-plot of principal component coefficients and scores for first two principal components
Vector Machines are possible candidates for successful classification.

The selected classification technique was two-layer feed forward neural network with \textit{Tanh} transfer functions, utilizing a scaled conjugate algorithm \cite{Moller1993}. The input was a 145x(1-8) matrix, 145 samples and (1-8) for the features, which was divided in two stages. The first stage was to keep 50\% of the data separate in order to retest each network’s performance in presence of new data, while the second stage was to use the remaining data divided by 85\% for training and 15\% for validation. It was evident from similar literature that the sample size was more than enough for the classification task, and the results would be more objective if the testing group would be large. There were cases with less than 20 class samples \cite{Blackledge2008} while in this sample group...
the average class size was 48. The same test sample group was kept separate from any training or validation for all the neural networks trained and tested in this research. This was done in order to have objective comparisons between the different neural network topologies and inputs. The topology used for testing each individual feature was 1-2-3 (first number is the input features, second is the hidden neurons, third is the outputs). The hidden layer size was tested empirically and $\text{Inputs} + 1$ (Heaton, 2008) was performing well in the experiments. The outputs were in binary format (1-0-0 for Non-Defective, 0-1-0 for Blisters and 0-0-1 for Scratches). Before proceeding with the final results the features were calculated individually using the traditional GLCM approach, where the features are extracted directly from the original image’s statistical texture measures. To make a direct comparison, a calculation of the features from the edge magnitude of the image followed. Features were tested individually to access the performance of each one and find the most significant features. Then they were paired in groups considering the performance of each individual feature. The results provided are over an average of 100 training sessions, with the average Mean Squared Error and Accuracy presented in Table 5.1.

The most interesting feature is $\text{Correlation}$ obtained using $\theta = 0^\circ$, $d = 1$ and $\theta = 90^\circ$, $d = 1$. The $\text{Correlation}$, $\text{Correlation90}$ and $\text{Contrast90}$ obtained from GLCM provide the highest accuracy, which implies they are the strongest features. Similar performance to those features is obtained from $\text{Contrast}$, $\text{Contrast90}$, $\text{Energy}$ and $\text{Homogeneity}$ in the GOCM case. $\text{Correlation and Correlation90}$ have exceptionally high accuracy when they derive from the edge magnitude.

Table 5.2 summarizes the tested networks with the statistical features’ combinations and resulting topologies. The best performing combination of GLCM features is 8-9-3 with an accuracy of 79.5%. It is observed that the accuracy increases while more features from the GLCM are introduced. On the contrary, there is an interesting observation to be made for GOCM features, $\text{Correlation and Correlation90}$ in pair are the best combination regarding accuracy. None of the other combinations achieves this high accuracy, because the information provided by the other data proves to be redundant. The computational load
Table 5.2: Artificial Neural Network topology table with MSE and Accuracy values over an average of 100 tested ANNs for each feature group. (Legend: C=Contrast, C90=Contrast90, E=Energy, E90=Energy90, H=Homogeneity, H90=Homogeneity90, Cr=Correlation, Cr90=Correlation90)

<table>
<thead>
<tr>
<th>ANN topologies</th>
<th>Features</th>
<th>GLCM MSE</th>
<th>GLCM Accuracy</th>
<th>GOCM MSE</th>
<th>GOCM Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-3-3</td>
<td>Cr,Cr90</td>
<td>0.1682</td>
<td>65.8</td>
<td>0.0353</td>
<td>98.6</td>
</tr>
<tr>
<td>3-4-3</td>
<td>Cr,Cr90,C</td>
<td>0.1631</td>
<td>63.0</td>
<td>0.0356</td>
<td>97.3</td>
</tr>
<tr>
<td>3-4-3</td>
<td>Cr,Cr90,E</td>
<td>0.1604</td>
<td>65.8</td>
<td>0.0385</td>
<td>98.6</td>
</tr>
<tr>
<td>3-4-3</td>
<td>Cr,Cr90,E90</td>
<td>0.1545</td>
<td>63.0</td>
<td>0.0385</td>
<td>97.3</td>
</tr>
<tr>
<td>3-4-3</td>
<td>Cr,Cr90,H</td>
<td>0.1656</td>
<td>64.4</td>
<td>0.0362</td>
<td>97.3</td>
</tr>
<tr>
<td>3-4-3</td>
<td>Cr,Cr90,H90</td>
<td>0.1697</td>
<td>63.0</td>
<td>0.0360</td>
<td>97.3</td>
</tr>
<tr>
<td>4-5-3</td>
<td>C,C90,E,E90</td>
<td>0.1579</td>
<td>64.4</td>
<td>0.1406</td>
<td>74.0</td>
</tr>
<tr>
<td>4-5-3</td>
<td>C,C90,H,H90</td>
<td>0.1452</td>
<td>71.2</td>
<td>0.1366</td>
<td>76.7</td>
</tr>
<tr>
<td>4-5-3</td>
<td>C,C90,Cr,Cr90</td>
<td>0.1490</td>
<td>65.8</td>
<td>0.0232</td>
<td>97.3</td>
</tr>
<tr>
<td>5-6-3</td>
<td>C,C90,E,Cr,Cr90</td>
<td>0.1218</td>
<td>78.1</td>
<td>0.0224</td>
<td>97.3</td>
</tr>
<tr>
<td>6-7-3</td>
<td>C,C90,H,H90,E,E90</td>
<td>0.1430</td>
<td>75.3</td>
<td>0.1229</td>
<td>82.2</td>
</tr>
<tr>
<td>6-7-3</td>
<td>C,C90,E,E90,Cr,Cr90</td>
<td>0.1287</td>
<td>78.1</td>
<td>0.0201</td>
<td>97.3</td>
</tr>
<tr>
<td>8-9-3</td>
<td>C,C90,H,H90,E,E90,Cr,Cr90</td>
<td>0.1182</td>
<td>79.5</td>
<td>0.0244</td>
<td>97.3</td>
</tr>
</tbody>
</table>

for each image of 150x150 pixels using 6bit scale for the 8 statistical features of gray-level gradient co-occurrence matrices with the Sobel calculation for the gradient was on average 30ms on an Intel 4770k processor at 4.2GHz.

5.2 Case study: A four class problem

![Class distribution of the sample set](image)

The sample set increased to 186 images of 150x150 pixels in 8bit gray-scale with 8
features each, distributed in four categories: non-defective (32%); blisters (29%); scratches (18%); and die lines (22%), with their distribution shown in Figure 5.6. The samples are surface images of industrial produced aluminum from a hot extrusion factory, from the same sample set as the previous case study, with the addition of die line defects. MVTec Halcon version 9.0 (an industrial machine vision tool) was used again to process the images and extract the feature matrices (source code in Appendix B). Matlab version 2012b was used to process the features matrices and allow different combinations of features to be used (source code in Appendix C). The dataset was normalized again to minimum and maximum values -1 and 1 respectively, with the following box-and-whisker diagram representing the original feature values (Figure 5.7). The scatter plots of some random pair of features show that the statistical features are also not linearly separable in this case study too (Figure 5.8).

![Figure 5.7: Box-and-whisker diagram of GOCM feature values](image_url)

The selected classification technique was again two-layer feed forward neural network with *Tanh* transfer functions, utilizing a scaled conjugate algorithm (Møller, 1993). The input was a 186x(1-16) matrix, 186 samples and 1-16 features, which was divided in two
Figure 5.8: Scatter plots of a random selection of GOCM features

stages. The first stage was to keep 50% of the data separate in order to retest each network’s performance in presence of new data, while the second stage was to use the remaining data divided by 85% for training and 15% for validation. It was evident from similar literature that the sample size was more than enough for the classification task, and the results would be more objective if the testing group would be large. There were cases with less than 20 class samples [Blackledge and Dubovitsky, 2008] while in this sample group the average class size was 46. The same test sample group was kept separate from any training or validation for all the neural networks trained and tested in this research. This was done
in order to have objective comparisons between the different neural network topologies and inputs. In this case study the number of features was doubled to 16, this was done to include the directions $\theta = 45^0$ and $\theta = 135^0$. Using all the available directions from the co-occurrence matrix will give more insight to proper selection of features for aluminium surface defect detection, while pixel pair distance was kept at $d = 1$. The topology used for testing each individual feature was 1-2-3 (first number is the input features, second is the hidden neurons, third is the outputs). The hidden layer size was tested empirically for size and $Inputs + 1$ [Heaton, 2008] resulted in good performance in the experiments. The outputs were in binary format (1-0-0-0 for Non-Defective, 0-1-0-0 for Blisters, 0-0-1-0 for Scratches and 0-0-0-1 for Die Lines). Before proceeding with the final results, a calculation of the features individually was made using the traditional GLCM method, where the features are extracted directly from the original image’s statistical texture measures. To make a direct comparison, a calculation of the statistical texture features from GOCM method followed. Features were tested individually to access the performance of each one and find the most significant features. Then they were paired in groups considering the performance of each individual feature. The results provided are over an average of 100 training sessions, with the average Mean Squared Error and Accuracy presented in Table 5.3.

In the previous case study there was not a single feature from GLCM that provided higher accuracy than the respective feature from GOCM. Correlation features provided higher accuracy compared to the rest of the features in both GLCM and GOCM. As a fourth class was introduced the complexity of the problem grew, changing the performance of each individual feature. As observed from Table 5.3 Correlation is still the best performing feature category in GOCM, while both Contrast and Correlation categories give average results in GLCM. For GLCM Contrast category, better accuracy is obtained at directions $\theta = 0^0$ and $\theta = 90^0$, while for GOCM at the directions of $\theta = 45^0$ and $\theta = 135^0$. The feature providing the highest accuracy for GLCM is Correlation with 55.9\%, compared to Correlation135 for GOCM where the provided accuracy is 81.7\%. The resistance to
Table 5.3: Artificial Neural Network topology table with MSE and Accuracy values over an average of 100 tested ANNs for each feature.

<table>
<thead>
<tr>
<th>Ann Topology</th>
<th>Features</th>
<th>GLCM MSE</th>
<th>GLCM Accuracy</th>
<th>GOCM MSE</th>
<th>GOCM Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-2-4</td>
<td>2-Contrast</td>
<td>0.1748</td>
<td>50.5</td>
<td>0.1765</td>
<td>39.8</td>
</tr>
<tr>
<td>1-2-4</td>
<td>2-Contrast45</td>
<td>0.1726</td>
<td>46.2</td>
<td>0.1678</td>
<td>55.9</td>
</tr>
<tr>
<td>1-2-4</td>
<td>2-Contrast90</td>
<td>0.1695</td>
<td>51.6</td>
<td>0.1744</td>
<td>38.7</td>
</tr>
<tr>
<td>1-2-4</td>
<td>2-Contrast135</td>
<td>0.1783</td>
<td>31.2</td>
<td>0.1724</td>
<td>47.3</td>
</tr>
<tr>
<td>1-2-4</td>
<td>2-Correlation</td>
<td>0.1700</td>
<td>55.9</td>
<td>0.1387</td>
<td>65.6</td>
</tr>
<tr>
<td>1-2-4</td>
<td>2-Correlation45</td>
<td>0.1751</td>
<td>45.2</td>
<td>0.1143</td>
<td>78.5</td>
</tr>
<tr>
<td>1-2-4</td>
<td>2-Correlation90</td>
<td>0.1728</td>
<td>54.8</td>
<td>0.1132</td>
<td>78.5</td>
</tr>
<tr>
<td>1-2-4</td>
<td>2-Correlation135</td>
<td>0.1743</td>
<td>43.0</td>
<td>0.1007</td>
<td>81.7</td>
</tr>
<tr>
<td>1-2-4</td>
<td>Energy</td>
<td>0.1866</td>
<td>26.9</td>
<td>0.1710</td>
<td>50.5</td>
</tr>
<tr>
<td>1-2-4</td>
<td>Energy45</td>
<td>0.1775</td>
<td>35.5</td>
<td>0.1749</td>
<td>44.1</td>
</tr>
<tr>
<td>1-2-4</td>
<td>Energy90</td>
<td>0.1868</td>
<td>26.9</td>
<td>0.1754</td>
<td>31.2</td>
</tr>
<tr>
<td>1-2-4</td>
<td>Energy135</td>
<td>0.1768</td>
<td>38.7</td>
<td>0.1747</td>
<td>49.5</td>
</tr>
<tr>
<td>1-2-4</td>
<td>Homogeneity</td>
<td>0.1852</td>
<td>22.6</td>
<td>0.1773</td>
<td>34.4</td>
</tr>
<tr>
<td>1-2-4</td>
<td>Homogeneity45</td>
<td>0.1825</td>
<td>30.1</td>
<td>0.1808</td>
<td>29.0</td>
</tr>
<tr>
<td>1-2-4</td>
<td>Homogeneity90</td>
<td>0.1796</td>
<td>49.5</td>
<td>0.1759</td>
<td>49.5</td>
</tr>
<tr>
<td>1-2-4</td>
<td>Homogeneity135</td>
<td>0.1837</td>
<td>29.0</td>
<td>0.1788</td>
<td>32.3</td>
</tr>
</tbody>
</table>

Illumination by the gradient magnitude of the images is responsible for the higher accuracies observed.

In Table 5.4 a wide variety of combinations was tested. The first seven networks tested were based on an increasing number of features for each method, based on their accuracy ranking in Table 5.3. The first network consists of the two features that provided the two highest accuracies, followed by the second network with the third highest ranking feature, etc. The accuracy is increasing in both cases until the information provided from including extra features is redundant. For GLCM the best combination was $C, C90, C_r, C_r90$ with 52.7% testing accuracy, while for GOCM $C_r, C_{r45}, C_{r90}, C_{r135}$ with 96.8%. The next few networks were based on feature groups, so each group consists only from one feature in all four possible directions ($\theta$). For both GLCM and GOCM the best performing group was Correlation, providing respectively 51.6% and 96.8% accuracy. The last few tested networks used the best performing feature group in combination with one of the other, while the last network tested utilized all 16 of the features. In both cases the highest
accuracy was provided by combining Contrast and Correlation groups. For the GLCM method the accuracy obtained was 55.9%, which was the highest of any other combination. For the GOCM method the highest accuracy was 98.9%.

5.3 Summary

This chapter was divided in two case studies. The first one contained three distinct classes; blisters, scratches and non-defective surfaces, while the second case study added die-lines as a fourth class. The results from the first case study showed that the created methodology’s features (GOCM) had great potential, achieving 98.6% accuracy using only two features in contrast to the GLCM features where the accuracy reached 79.5% using all 8 of the features. For the second case study, die-lines were added in the classification along with 8 more features. 98.9% accuracy was achieved using a combination of 8 GOCM features in comparison to 55.9% accuracy for the GLCM statistical features. GOCM showed that for added complexity, a greater number of features is required but was still capable of achieving very high accuracy, outperforming GLCM. In the next chapter the work presented in this research will be concluded and discussed, along with suggestions for further research opportunities and future directions.
Table 5.4: Artificial Neural Network topology table with MSE and Accuracy values over an average of 100 tested ANNs for each feature group. (Legend: C=Contrast, E=Energy, H=Homogeneity, Cr=Correlation)

<table>
<thead>
<tr>
<th>Ann Topology</th>
<th>Features</th>
<th>GLCM</th>
<th>Features</th>
<th>GOCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-3-4</td>
<td>Cr,Cr90</td>
<td>0.1650</td>
<td>45.2</td>
<td>Cr45,Cr135</td>
</tr>
<tr>
<td>3-4-4</td>
<td>C90,Cr,Cr90</td>
<td>0.1569</td>
<td>49.5</td>
<td>Cr45,Cr90,Cr135</td>
</tr>
<tr>
<td>4-5-4</td>
<td>C,C90,Cr,Cr90</td>
<td>0.1426</td>
<td>52.7</td>
<td>Cr,Cr45,Cr90,Cr135</td>
</tr>
<tr>
<td>5-6-4</td>
<td>C,C90,Cr,Cr90,H90</td>
<td>0.1405</td>
<td>52.7</td>
<td>C45,Cr,Cr45,Cr90,Cr135</td>
</tr>
<tr>
<td>6-7-4</td>
<td>C,C45,C90,Cr,Cr90,H90</td>
<td>0.1385</td>
<td>49.5</td>
<td>C45,Cr,Cr45,Cr90,Cr135,E</td>
</tr>
<tr>
<td>7-8-4</td>
<td>C,C45,C90,Cr,Cr45,Cr90,H90</td>
<td>0.1371</td>
<td>49.5</td>
<td>C45,Cr,Cr45,Cr90,Cr135,E,H90</td>
</tr>
<tr>
<td>8-9-4</td>
<td>C,C45,C90,Cr,Cr45,Cr90,Cr135,H90</td>
<td>0.1371</td>
<td>50.5</td>
<td>C45,Cr,Cr45,Cr90,Cr135,E,E135,H90</td>
</tr>
<tr>
<td>4-5-4</td>
<td>C,C45,C90,C135</td>
<td>0.1556</td>
<td>48.4</td>
<td>C,C45,C90,C135</td>
</tr>
<tr>
<td>4-5-4</td>
<td>Cr,Cr45,Cr90,Cr135</td>
<td>0.1558</td>
<td>51.6</td>
<td>Cr,Cr45,Cr90,Cr135</td>
</tr>
<tr>
<td>4-5-4</td>
<td>E,E45,E90,E135</td>
<td>0.1735</td>
<td>38.7</td>
<td>E,E45,E90,E135</td>
</tr>
<tr>
<td>4-5-4</td>
<td>H,H45,H90,H135</td>
<td>0.1732</td>
<td>38.7</td>
<td>H,H45,H90,H135</td>
</tr>
<tr>
<td>8-9-4</td>
<td>Cr,Cr45,Cr90,Cr135,C,C45,C90,C135</td>
<td>0.1399</td>
<td>55.9</td>
<td>Cr,Cr45,Cr90,Cr135,C,C45,C90,C135</td>
</tr>
<tr>
<td>8-9-4</td>
<td>Cr,Cr45,Cr90,Cr135,E,E45,E90,E135</td>
<td>0.1484</td>
<td>50.5</td>
<td>Cr,Cr45,Cr90,Cr135,E,E45,E90,E135</td>
</tr>
<tr>
<td>8-9-4</td>
<td>Cr,Cr45,Cr90,Cr135,H,H45,H90,H135</td>
<td>0.1574</td>
<td>48.4</td>
<td>Cr,Cr45,Cr90,Cr135,H,H45,H90,H135</td>
</tr>
<tr>
<td>16-17-4</td>
<td>All</td>
<td>0.1337</td>
<td>52.7</td>
<td>All</td>
</tr>
</tbody>
</table>
Chapter 6 Contribution and Conclusion

6.1 Summary of the research

The aim of this research was to provide the aluminium extrusion industry with means to accurately detect surface defects early in the production stage, even as soon as the profiles are extruded. The advantage of early detection is to adjust the process parameters in order to counter the appearance of defects. Initially a sample set was collected from industrially extruded aluminium profile surfaces. Image processing and statistical texture feature extraction was applied to the sample, following techniques that were applied to similar fields. Extracted feature analysis was performed on the impact of defects on the features’ values. A novel technique (GOCM) was developed that provided better results than the widely adopted GLCM technique, while both were tested extensively with a combination of features and each feature one by one. As a final step it was proven that the developed technique is more effective for the application.

6.2 Resolution of research aims and objectives

The summary of the objectives from Introduction is listed below, along with the assessment of the work for each one:
- To investigate aluminium extrusion surface defects and relevant feature extraction techniques.

An extensive literature review was performed prior to image processing, in order to assess the current state of techniques for feature extraction found in the literature. Different techniques were used on the sample set, but most were infeasible to use. Some techniques were dependant on the illumination (especially techniques which involved thresholding), which was chosen to fit the needs of the industry for ease of installation, be repairable, have easy to perform maintenance and have low cost, and as such they couldn’t be used. GLCM statistical features were fit for the application but the information provided didn’t result in acceptable accuracy rates of classification.

- To create a system that acquires images from aluminium surfaces.

This objective involved researching what was the current technological advances in electronic hardware in 2008. The latest interface was Gigabit Ethernet which offered high transfer speeds and compatibility with current networking infrastructure in the industry. Therefore a suitable image and video capturing device was selected that conformed to the GigE Vision standard that utilized Gigabit Ethernet connection. The selected imaging device was a Basler Scout scA1000-32gm GigE gray-scale camera with a resolution of 1296x966 pixels. The illumination consisted of Fluorescent lighting which is usually found in industrial environments, and was chosen for the simplicity of installation and ease of replacement. For the image acquisition computer an Intel Core 2 Duo processor at 3.2Ghz was used. For the feature extraction and neural network training an Intel i7 4770k quad core processor clocked at 4.2 Gigahertz was used along with 16 Gigabytes of RAM (Random Access Memory). The speed offered by current technology was substantial, needing only 30-32ms of processing time for processing an image and extracting the feature set, which enables the system to be used for on-line monitoring and quality control.

- To obtain a sample set from extruded aluminium profiles.
The sample set used in this research was industrially extruded aluminium profiles of alloys 6063 and 6061. The samples contained non-defective surfaces, blisters, scratches and die-lines. Every defect was due to extrusion parameter errors and handling errors. There was no forced defective samples or artificially created ones through usage of an imaging software. The sample set was not manipulated or altered with the usage of computer software, in a way that the images could have forced gray values or altered in any way, except for noise filtering, which was performed by the industrial machine vision software MVtech Halcon 9.0. This way the sample set was representative of the realistic application of a machine vision at the stage of extrusion, since the images’ integrity was unaltered.

- **To improve the established techniques or develop a new one, improving the accuracy of the classification.**

A novel technique was developed, based on the established GLCM statistical features. The technique was named Gradient Only Co-occurrence Matrices. Instead of using the original image, or a combination of the original image and the image’s gradient magnitude, GOCM utilizes only the image’s gradient magnitude after its values have undergone a real ($\mathbb{R}$) to integer ($\mathbb{Z}$) transformation. The technique proved to provide very high accuracy rates, while being resistant to large inconsistencies in image gray-scale value distributions. When adding an additional class to the classification, therefore making the problem more complex, GLCM failed to retain the accuracy rates they provided with the three-class case study, while GOCM kept similar detection rates, albeit with the addition of extra features. The developed method can be applied to the aluminium extrusion quality control as proven by the results in Chapter 5. The method can be used in commercial machine vision software or can be reproduced in a programming language, therefore the application is not limited to the software used in this research. As it is a method that extracts features from textures, it could be used for other applications, although currently it is only tested for extruded aluminium surfaces and as such the success of the application in
6.3 Contributions

The main contribution of this research was to provide a methodology for surface quality inspection of extruded aluminium profiles. This contribution can be broken down to:

• Investigation of the literature on the field of automated visual quality inspection on the surface of extruded aluminium profiles. The literature proved to be lacking compared to similar fields.

• Development and creation of a system with industrial application. The samples used were not artificially produced, but rather obtained from an extrusion facility.

• Extraction of GLCM statistical texture features and application on the sample set with an exhaustive variety of tested combinations, including each feature one by one.

• Design and application of a novel approach (Gradient Only Co-occurrence matrices) to statistical feature extraction from co-occurrence matrices, which doesn’t extract the information from the original image, but from the gradient magnitude of the original image after its values are transformed from real ($\mathbb{R}$) to integer ($\mathbb{Z}$).

• Comparison between GLCM and GOCM features using each feature one by one and an exhaustive combination of tested neural network topologies.

• Design of a novel texture classification methodology for industrial use, which is easy to implement and provides high accuracy for the selected task.

• Submitted a journal article which was subject to amendments and is currently under review.
6.4 Discussion

In this research, a computer vision-based system for inspection of surface defects on aluminum profiles was developed. Initially, the study focused on two defects, blisters and scratches and classified them in three classes (non-defective, blister, scratch). A feature selection was performed for this application, which resulted in very high accuracy using only 2 features. This high detection accuracy is achieved combining the current literature on the field with a novel approach on selecting and manipulating variables, such as obtaining values from the statistical features of co-occurrence matrices on the gradient magnitude of the image as a result of the Sobel operator. This matrix was named GOCM, in order to be able to distinguish it between the traditional GLCM and GLGCM approaches. Even if the nature of the aluminum surface texture is near-stochastic, which makes defect detection especially difficult, it was proven that using statistical features from the GOCM is more suitable in extruded aluminum surface inspection. More samples were added at a later stage containing Die-Lines type of defects. GLCM achieved even lower accuracy than the 3 class case study, while GOCM achieved high accuracy rates (98.9%) with the usage of more statistical texture features. Since the sample images were purposely varied in terms of gray-level value distribution, GOCM revealed another advantage, utilizing the gradient’s partial resistance to illumination, to provide textural features that could be used for classification in tasks where even illumination of the object and uniform contrast levels cannot be achieved.

The extruded aluminum surface defect recognition is a problem that isn’t investigated thoroughly in the literature and for a comparison to be made one needs to look in similar fields. The closest research, done by Zheng et al. (2002), used aluminum samples (although not extruded products), and studied hole and crack defects. Genetic algorithms were used to obtain optimal morphology processing parameters and the resulting accuracy was 91% for hole defects and 86% for crack defects out of 100 samples. On a similar case of copper strips, Xue-Wu et al. (2011) developed a support vector machine classifier based on features
obtained from texture spectral measures, with 85% testing accuracy for 7 types of defects on a sample size of 420. The proposed method outperforms the first example by achieving up to 98.9% accuracy, while an indirect comparison with the second research shows great potential, although a definite conclusion is impossible due to different complexities (4 vs 7 classes) and surface properties.

6.5 Future Directions

A list of suggestions to enhance, expand and diversify the research presented here follows:

• The types of defects available for this research didn’t include all possible surface defects of extruded aluminium profiles. It is difficult to assemble a complete defect sample set and a long period of time is needed to create a database containing every possible case. It is very costly for an extrusion company to adjust the process parameters to create defects on purpose (loss of manufacturing capacity and high cost in scrap). It would be wise for interested parties to begin collecting defective samples with rare appearance.

• The defect classification performed was on unprocessed extruded aluminium surfaces. As defects still appear after anodizing or powder coating (or other painting processes), it would be beneficial to the industry to research methods of detection and classification of painting defects (either those that are made visible during this stage, or those that are generated during painting processes).

• As this research’s focus was on the suitability of feature selection for visual inspection of extruded aluminium surfaces, there were time constraints for investigating different classification methods and their effective accuracy rates. An investigation of different techniques could be performed in the future, such as using Support Vector Machines, other architectures of Artificial Neural Networks or other pattern recognition techniques.
• The novel developed technique (GOCM) was applied to extract statistical texture features from aluminium surfaces. It would be possible for the technique to provide high accuracy on other classification cases, such as for defects in copper or steel products, or even in different areas such as satellite imaging, or other textural classification cases. Therefore, further investigation of GOCM is needed.

• The proposed technique could also be tested using standard texture benchmarks developed specifically for this purpose, thus examining the suitability of the method in wider application.
Bibliography


Appendix A Interview

This is a personal interview with the CEO of Exalco S.A, Mr. Ioannis Kantonias. Exalco S.A is a Greek aluminium extrusion company which was kind enough to provide the hardware, the software and the samples used in this research.

1. *Can you tell us a few words about Exalco S.A?*

   Exalco S.A. is one of the greatest aluminum industries in Greece, was founded in 1973 with its main headquarters in Larissa. Having established a long and successful presence at the Greek aluminum history, the company’s name is linked with the tradition, experience, development and quality of its products and services. Exalco S.A. is an integrated industrial unit, producing aluminum profiles and has developed an extended sales network in domestic and foreign markets.

2. *What is the capacity of production for Exalco S.A annually?*

   Its plant [51,228 sq.m.] at privately owned fields of 178,872 sq.m. which are located in Larissa include: Extrusion units containing four presses of 1,100 tones, 1,750 tones, 2,200 tones and 2,840 tones respectively, with production capacity of 33,000 tones annually, as well as a section producing extrusion dies. Surface treatment and anodizing unit with fully automated machinery with capacity of 6,000 tones annually, offering high quality levels. Vertical Powder Coating unit producing 10,100 tones annually. Horizontal Powder Coating unit producing 5,000 tones annually. Powder Coating unit in wood, marble and granite and fantasy decoration, by the qualified system V.I.V. DECORAL with annual production capacity 1,000 tones. Foundry unit with capacity of 12,000 tones annually.

3. *Which are the main types of industries Exalco S.A does business with?*

   Main types of industries using our products are: construction companies, greenhouse developers, ladder-scaffolding industries, truck platform manufacturers, refrigeration industries etc.
4. *How important is the quality of the finished product and what sort of quality control is used at the moment?*


5. *What percentage of the total defects the surface quality ones amount to? What is the cost of them?*

The percentage of the surface defects to the total defects is about 13% in quantity and 30% in frequency. The Cost of them is about 100,000 € annually.

6. *If a surface quality control system was applied, capable of detecting defects as the products exit the press, how would that be beneficial to the company?*

The benefits of applying a quality control system are a) To identify the defect in the beginning of production b) To avoid the defects by taking quick actions c) Understand immediately the source of the defect, and finally d) The faulty product will not reach the customer.

7. *How detrimental to the painted aluminum surface are those defects?*

Depends of the defect, but generally speaking the painting shouldn’t be as good as it should be and some times the entire lot will be rejected with the consequent results of reproducing the product, increasing the scrap, delays e.t.c

8. *What would you want from a surface quality control system?*

The ability from a surface quality control system to identify the majority of the surface defects (If it is possible all of them) to classify them and to be able to be installed in the beginning of the production of the extrusion process.
Appendix B Halcon code

```cpp
#include "HalconCpp.h"

#ifndef NO_EXPORT_MAIN
// Main procedure
void action()
{
    using namespace Halcon;

    // Local iconic variables
    HObject Image, ImageResult, EdgeAmplitude, ImageScaleMax;
    HObject Region1, Rectangle, Image1, Region, RegionClosing;
    HObject ConnectedRegions1, SelectedRegions2, Skeleton,
                   Contours;
    HObject BinImage;

    // Local control variables
    HTuple MatrixID, j, i, a, b, c, Compactness;
    HTuple Convexity, Circularity, Angle, Area, Row, Column;
    HTuple Row1, Column1, Row2, Column2, Diameter, Energy2;
    HTuple Correlation2, Homogeneity2, Contrast2, Energy3;
    HTuple Correlation3, Homogeneity3, Contrast3, Energy4;
    HTuple Correlation4, Homogeneity4, Contrast4, Energy5;
```
HTuple Correlation5, Homogeneity5, Contrast5, Entropy;
HTuple Anisotropy, Energy6, Correlation6, Homogeneity6;
HTuple Contrast6, Energy7, Correlation7, Homogeneity7;
HTuple Contrast7, Energy8, Correlation8, Homogeneity8;
HTuple Contrast8, Energy9, Correlation9, Homogeneity9;
HTuple Contrast9, Entropy2, Anisotropy2, Area4, Row8, Column8
\rightarrow;
HTuple Max4, Angle1, Angle2, Energy, Correlation, Homogeneity
\rightarrow;
HTuple Contrast, Energy1, Correlation1, Homogeneity1,
\rightarrow Contrast1;
HTuple TotalContrast, WindowHandle, e;

create_matrix(32, 186, 0, &MatrixID);
j = 1;
for (i=1; i<=186; i+=1)
{
    set_system("image_dir", "/Users/*******/Desktop/");
    read_image(&Image, "/Combined/"+(i.ToString("01")));
    convol_image(Image, &ImageResult, "lowpas_3_3", "mirrored");
    sobel_amp(ImageResult, &EdgeAmplitude, "sum_abs", 3);
    gen_rectangle1(&Rectangle, 0, 0, 150, 150);
    cooc_feature_image(Rectangle, EdgeAmplitude, 6, 0, &Energy2,
                        &Correlation2, &Homogeneity2, &Contrast2);
    cooc_feature_image(Rectangle, EdgeAmplitude, 6, 90, &Energy3,
                        &Correlation3, &Homogeneity3, &Contrast3);
\[
\text{cooc\_feature\_image}(\text{Rectangle}, \text{EdgeAmplitude}, 6, 45, \&\text{Energy4} \\
\quad, \\
\quad\&\text{Correlation4}, \quad\&\text{Homogeneity4}, \&\text{Contrast4});
\]
\[
\text{cooc\_feature\_image}(\text{Rectangle}, \text{EdgeAmplitude}, 6, 135, & \\
\quad\rightarrow\text{Energy5}, \\
\quad\&\text{Correlation5}, \quad\&\text{Homogeneity5}, \&\text{Contrast5});
\]
\[
\text{cooc\_feature\_image}(\text{Rectangle}, \text{Image}, 6, 0, &\text{Energy6}, \\
\quad&\text{Correlation6}, \quad&\text{Homogeneity6}, \quad&\text{Contrast6});
\]
\[
\text{cooc\_feature\_image}(\text{Rectangle}, \text{Image}, 6, 90, &\text{Energy7}, \\
\quad&\text{Correlation7}, \quad&\text{Homogeneity7}, \quad&\text{Contrast7});
\]
\[
\text{cooc\_feature\_image}(\text{Rectangle}, \text{Image}, 6, 45, &\text{Energy8}, \\
\quad&\text{Correlation8}, \quad&\text{Homogeneity8}, \quad&\text{Contrast8});
\]
\[
\text{cooc\_feature\_image}(\text{Rectangle}, \text{Image}, 6, 135, &\text{Energy9}, \\
\quad&\text{Correlation9}, \quad&\text{Homogeneity9}, \quad&\text{Contrast9});
\]

\[j \ += \ 1;\]
\[e = i - 1;\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 0, e, \text{Contrast2});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 1, e, \text{Contrast3});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 2, e, \text{Energy2});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 3, e, \text{Energy3});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 4, e, \text{Correlation2});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 5, e, \text{Correlation3});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 6, e, \text{Homogeneity2});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 7, e, \text{Homogeneity3});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 8, e, \text{Contrast4});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 9, e, \text{Contrast5});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 10, e, \text{Energy4});
\]
\[
\text{set\_value\_matrix} (\text{MatrixID}, 11, e, \text{Energy5});
\]
```cpp
set_value_matrix(MatrixID, 12, e, Correlation4);
set_value_matrix(MatrixID, 13, e, Correlation5);
set_value_matrix(MatrixID, 14, e, Homogeneity4);
set_value_matrix(MatrixID, 15, e, Homogeneity5);
set_value_matrix(MatrixID, 16, e, Contrast6);
set_value_matrix(MatrixID, 17, e, Contrast7);
set_value_matrix(MatrixID, 18, e, Energy6);
set_value_matrix(MatrixID, 19, e, Energy7);
set_value_matrix(MatrixID, 20, e, Correlation6);
set_value_matrix(MatrixID, 21, e, Correlation7);
set_value_matrix(MatrixID, 22, e, Homogeneity6);
set_value_matrix(MatrixID, 23, e, Homogeneity7);
set_value_matrix(MatrixID, 24, e, Contrast8);
set_value_matrix(MatrixID, 25, e, Contrast9);
set_value_matrix(MatrixID, 26, e, Energy8);
set_value_matrix(MatrixID, 27, e, Energy9);
set_value_matrix(MatrixID, 28, e, Correlation8);
set_value_matrix(MatrixID, 29, e, Correlation9);
set_value_matrix(MatrixID, 30, e, Homogeneity8);
set_value_matrix(MatrixID, 31, e, Homogeneity9);
}
}

#ifndef NO_EXPORT_APP_MAIN
int main(int argc, char *argv[])
{
    using namespace Halcon;
    // Default settings used in HDevelop (can be omitted)
    set_system("do_low_error","false");
```
action();
    return 0;
}
#endif
#endif
#endif
 Appendix C  Matlab code

/// Data Division

inputs2 = GOCMFeatureMatrix';

inputs = GLCMFeatureMatrix';

targets = Classes186';

Q = size(inputs,2);
Q1 = floor(Q*0.50);
Q2 = Q - Q1;
ind = randperm(Q);
ind1 = ind(1:Q1);
ind2 = ind(Q1+(1:Q2));
x1 = inputs(:,ind1);
x1s = inputs2(:,ind1);
t1 = targets(:,ind1);
x2 = inputs(:,ind2);
x2s = inputs2(:,ind2);
t2 = targets(:,ind2);

/// GLCM Neural Network

hiddenLayerSize = 17;
net = patternnet(hiddenLayerSize);

net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 85/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 0/100;

% For help on training function 'trainlm' type: help trainlm
% For a list of all training functions type: help nntrain
net.trainFcn = 'trainscg';

% Choose a Performance Function
% For a list of all performance functions type: help
    ← nnperformance
net.performFcn = 'mse';  % Mean squared error
net.trainParam.epochs = 10000;

var = [1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16]
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist',
    ← ...
    'plotregression', 'plotfit'};
numNN = 100;
nets = cell(1,numNN);
tr = cell(1,numNN);
% Train the Network
for i=1:numNN
    disp([‘Training’ num2str(i) ‘/’ num2str(numNN)])
    [nets{i},tr{i}] = train(net,x1(var,:),t1);
end

% Test the Network
perfs = zeros(1,numNN);
y2Total = 0;
for i=1:numNN
    neti = nets{i};
    y2 = neti(x2(var,:));
    perfs(i) = mse(neti,t2,y2);
    y2Total = y2Total + y2;
end
perfs
y2AverageOutput = y2Total / numNN;
perfAveragedOutputs = mse(nets{1},t2,y2AverageOutput);

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotconfusion(targets,outputs,'ALL',trainTargets,
→ outputs,'Train',valTargets,outputs,'Validation',testTargets
%figure, ploterrhist(errors)

perfAveragedOutputs

plotconfusion(t2,y2AverageOutput)

////////////////////////////////////////////////////////
/// GOCM Neural Network
////////////////////////////////////////////////////////

hiddenLayerSize = 17;
net = patternnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 85/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 0/100;

% For help on training function 'trainlm' type: help trainlm
% For a list of all training functions type: help nntrain
net.trainFcn = 'trainscg';

% Choose a Performance Function
% For a list of all performance functions type: help
    ↪ nnperformance
net.performFcn = 'mse'; % Mean squared error
net.trainParam.epochs = 1000;

var = [1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16]
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist',
                ↪ ...'
                'plotregression', 'plotfit'};

numNN = 100;
ets = cell(1,numNN);
tr = cell(1,numNN);
% Train the Network
for i=1:numNN
    disp(['Training' num2str(i) '/\num2str(numNN)'])
[nets{i},tr{i}] = train(net,x1s(var,:),t1);
end

% Test the Network
perfs = zeros(1,numNN);
y2Total2 = 0;
for i=1:numNN
    neti = nets{i};
y2 = neti(x2s(var,:));
    perfs(i) = mse(neti,t2,y2);
y2Total2 = y2Total2 + y2;
end
perfs

y2AverageOutput2 = y2Total2 / numNN;

perfAveragedOutputs2 = mse(nets(1),t2,y2AverageOutput2);

%% Plots
%% Uncomment these lines to enable various plots.

figure, plotperform(tr)
figure, plottrainstate(tr)
figure, plotconfusion(targets,outputs,'ALL',trainTargets,
  outputs,'Train',valTargets,outputs,'Validation',testTargets,
  outputs,'Test')
figure, ploterrhist(errors)

perfAveragedOutputs2
plotconfusion(t2,y2AverageOutput2)
Appendix D  Sample set

Figure D.1: Non-Defective
Figure D.2: Blisters

Figure D.3: Scratches
Figure D.4: Die-Lines
Appendix E  Ethical Review
Please complete and return the form to Research Section, Quality Management Division, Academic Registry, University House, with your thesis, prior to examination.

<table>
<thead>
<tr>
<th>Postgraduate Research Student (PGRS) Information</th>
<th>Student ID:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Candidate Name: Apostolos Chondronasios</td>
<td>410582</td>
</tr>
<tr>
<td>Department: ENG</td>
<td></td>
</tr>
<tr>
<td>First Supervisor: Dr Ivan Popov</td>
<td></td>
</tr>
<tr>
<td>Start Date: February 2009</td>
<td></td>
</tr>
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</table>

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<th>Study Mode and Route:</th>
<th>Part-time</th>
<th>MPhil</th>
<th>MD</th>
<th>PhD</th>
<th>Integrated Doctorate (NewRoute)</th>
<th>Prof Doc (PD)</th>
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| Title of Thesis:                   | Surface Quality Control of Extruded Aluminium Profiles using Pattern Recognition Techniques |

<table>
<thead>
<tr>
<th>Thesis Word Count:</th>
<th>16714</th>
</tr>
</thead>
<tbody>
<tr>
<td>(excluding ancillary data)</td>
<td></td>
</tr>
</tbody>
</table>

If you are unsure about any of the following, please contact the local representative on your Faculty Ethics Committee for advice. Please note that it is your responsibility to follow the University’s Ethics Policy and any relevant University, academic or professional guidelines in the conduct of your study. Although the Ethics Committee may have given your study a favourable opinion, the final responsibility for the ethical conduct of this work lies with the researcher(s).

**UKRIO Finished Research Checklist:**
(If you would like to know more about the checklist, please see your Faculty or Departmental Ethics Committee rep or see the online version of the full checklist at: [http://www.ukrio.org/what-we-do/code-of-practice-for-research/](http://www.ukrio.org/what-we-do/code-of-practice-for-research/))

<table>
<thead>
<tr>
<th>a) Have all of your research and findings been reported accurately, honestly and within a reasonable time frame?</th>
<th>YES</th>
</tr>
</thead>
<tbody>
<tr>
<td>b) Have all contributions to knowledge been acknowledged?</td>
<td>YES</td>
</tr>
<tr>
<td>c) Have you complied with all agreements relating to intellectual property, publication and authorship?</td>
<td>YES</td>
</tr>
<tr>
<td>d) Has your research data been retained in a secure and accessible form and will it remain so for the required duration?</td>
<td>YES</td>
</tr>
<tr>
<td>e) Does your research comply with all legal, ethical, and contractual requirements?</td>
<td>YES</td>
</tr>
</tbody>
</table>

*Delete as appropriate
**Candidate Statement:**

I have considered the ethical dimensions of the above named research project, and have successfully obtained the necessary ethical approval(s)

<table>
<thead>
<tr>
<th>Ethical review number(s) from Faculty Ethics Committee (or from NRES/SCREC):</th>
<th>7C06-0A95-652F-97C3-3A93-CCCE-EAEF-963F</th>
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<tbody>
<tr>
<td>Signed: (Student)</td>
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<tr>
<td>Date: 29/12/2014</td>
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</tbody>
</table>

If you have *not* submitted your work for ethical review, and/or you have answered ‘No’ to one or more of questions a) to e), please explain why this is so:

<table>
<thead>
<tr>
<th>Signed: (Student)</th>
<th>Date:</th>
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Certificate of Ethics Review

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<tr>
<th>Project Title:</th>
<th>Surface Quality Control of Extruded Aluminium Profiles using Pattern Recognition Techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td>User ID:</td>
<td>540789</td>
</tr>
<tr>
<td>Name:</td>
<td>Apostolos Chondronasios</td>
</tr>
<tr>
<td>Application Date:</td>
<td>28/12/2014 08:31:49</td>
</tr>
</tbody>
</table>

You must download your certificate, print a copy and keep it as a record of this review.

The chair person of the Technology Faculty Ethics Committee is John Williams.

It is your responsibility to adhere to the University Ethics Policy and any Department/School or professional guidelines in the conduct of your study including relevant guidelines regarding health and safety of researchers and University Health and Safety Policy.

It is also your responsibility to follow University guidance on Data Protection Policy:

- General guidance for all data protection issues
- University Data Protection Policy

You are reminded that as a University of Portsmouth Researcher you are bound by the UKRIO Code of Practice for Research; any breach of this code could lead to action being taken following the University`s Procedure for the Investigation of Allegations of Misconduct in Research.

Any changes in the answers to the questions reflecting the design, management or conduct of the research over the course of the project must be notified to the Faculty Ethics Committee. **Any changes that affect the answers given in the questionnaire, not reported to the Faculty Ethics Committee, will invalidate this certificate.**

This ethical review should not be used to infer any comment on the academic merits or methodology of the project. If you have not already done so, you are advised to develop a clear protocol/proposal and ensure that it is independently reviewed by peers or others of appropriate standing. A favourable ethical opinion should not be perceived as permission to proceed with the research; there might be other matters of governance which require further consideration including the agreement of any organisation hosting the research.

**GovernanceChecklist**  
**A1-BriefDescriptionOfProject:** This research investigates detection and classification of surface defects in extruded aluminium profiles in order to replace the traditional eye inspection which is still the method widely used today. Through an extensive literature review it is evident that extruded aluminium surface is not investigated properly, while similar industrial products such as copper strips or rolled steel have attracted more interest. It is important to not only detect a defect but locate it and classify it on the

**Certificate Code:** 7C06-0A95-652F-97C3-3A93-CCCE-EAEF-963F
workpiece. An experimental machine vision system is used to capture images. Extensive feature selection is investigated and appropriate statistical features from a novel technique based on Gradient-Only Co-occurrence Matrices are proposed to detect and classify defects. The developed methodology makes use of the Sobel edge detector to obtain the gradient magnitude of the image and is followed by the extraction of statistical texture measures from the gradient, after a transformation of the gradient values. Comparisons are made between the statistical features extracted from the original image (Gray-Level Co-occurrence Matrix) and those extracted from the gradient magnitude using a novel approach (Gradient-Only Co-occurrence Matrix). The features extracted from the image processing are classified by feed-forward artificial neural networks. Experiments were conducted for a three class and a four class case study, with the first consisting of Good Surface, Blisters and Scratches, and the second introducing Die Lines to the classes of the first case study. The artificial neural network training is tested using different combinations of statistical features with different topologies. Features are compared individually and grouped, showing better classification accuracy for the novel technique compared to research standard methodology of gray-level co-occurrence matrices.

A2-Faculty: Technology
A5-AlreadyExternallyReviewed: No
B1-HumanParticipants: No
HumanParticipantsDefinition
B2-HumanParticipantsConfirmation: Yes
C6-SafetyRisksBeyondAssessment: No
D2-PhysicalEcologicalDamage: No
D4-HistoricalOrCulturalDamage: No
E1-ContentiousOrIllegal: No
E2-SociallySensitiveIssues: No
F1-InvolvesAnimals: No
F2-HarmfulToThirdParties: No
G1-ConfirmReadEthicsPolicy: Confirmed
G2-ConfirmReadUKRIOCodeOfPractice: Confirmed
G3-ConfirmReadConcordatToSupportResearchIntegrity: Confirmed
G4-ConfirmedCorrectInformation: Confirmed

28/12/2014