UNIVERSITI PUTRA MALAYSIA

STEEL STRIPS SURFACE CLASSIFICATION AND DEFECT DETECTION BASED ON MULTIPLE INTEGRATED FEATURES AND CLASSIFICATION SCHEMES

MOHAMMED W. M. ASHOUR

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By

MOHAMMED W. M. ASHOUR

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Chairman : Associate Professor Fatimah Binti Khalid, PhD
Faculty : Computer Science and Information Technology

Machine vision has become an indispensable tool in automated steel surface inspection. Such technologies are able to facilitate or replace manual inspection methods with benefits such as manpower reduction and operator error minimization. In the last two decades, researchers have actively explored computer extractable visual features for steel surface inspection. However, existing approaches suffer from certain limitations that cause ineffectiveness. Specifically, (i) non-discriminating feature choices lead to poor inter-class separability; and (ii) classifier complexity coupled with high numbers of training epochs. Therefore, this research aims to propose two frameworks to improve the inspection performance of steel surface types.

The first framework performs two tasks for machined surface texture classification and identification. The first task generates the most discriminating feature representation for surface texture. This is achieved through the proposed feature extraction method DST-GLCM, which integrates the Discrete Shearlet Transform (DST) and the Gray Level Co-occurrence Matrix (GLCM), producing a compact yet discriminative feature representation. A two-level classification scheme is then proposed combining the capabilities of the Support Vector Machine (SVM) and a proposed Consecutive Training with Collective Testing Artificial Neural Network (CTCT-ANN) technique. The SVM-level classifies the surface images into six categories based on surface texture features. This is followed by the CTCT-ANN-level where each of the surface textured images are further classified into sub-categories according to their surface roughness. Finally, the surface roughness parameters for all classified images are estimated.

The second framework extracts and combines different features (global and local) from hot-rolled steel surface images of different forms into different domains (spatial and frequency). This improves the image content description and offers a variant representation of the surface image. This is useful for surface defect detection and classification. The global features are extracted from the input image using the proposed DST-GLCM (from Framework-1). Local features are extracted after dividing each input image into four blocks. Then, local features/descriptors namely the GLCM, Uniform Local Binary Pattern (ULBP) and Speeded-Up Robust Features (SURF) are extracted from every block. All the extracted global and local features are combined in a high dimensional feature vector, whose dimensionality is later reduced using Principal Components Analysis (PCA). The final classification is accomplished using an SVM.

Both frameworks are evaluated using two different datasets of steel surface images. The first framework uses Engineering Machined Textures (EMT) workpiece surface images produced using several machining processes. The second framework uses the Northeastern University (NEU) standard database that comprises surface images of hot-rolled steel strips with different defect types. The results in this research show improvement when compared with previous related studies. The maximum accuracy achieved in surface classification of EMT dataset was up to 100%, with a maximum error in surface roughness estimation of 0.004 micrometer. In addition, the maximum accuracy achieved in defect detection of NEU dataset was up to 99.34%.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

KLASIFIKASI PERMUKAAN DAN PENGESANAN KECACATAN PADA JALUR KELULI BERDASARKAN PELBAGAI CIRI BERSEPADU DAN SKEMA PENGKELASAN

Oleh

MOHAMMED W. M. ASHOUR

September 2018

Pengerusi : Profesor Madya Fatimah Binti Khalid, PhD
Fakulti : Sains Komputer dan Teknologi Maklumat

Teknologi penglihatan mesin menjadi alat yang sangat diperlukan dalam pemeriksaan permukaan keluli secara automatik. Teknologi sedemikian mampu membantu atau menggantikan kaedah pemeriksaan manual dengan faedah-faedah seperti pengurangan tenaga kerja dan pengurangan kesilapan operator. Dalam dua dekad yang lalu, para penyelidik dengan aktifnya telah meneroka ciri-ciri visual yang dapat diekstrak oleh komputer bagi pemeriksaan permukaan keluli. Walau bagaimanapun, pendekatan yang sedia ada mempunyai beberapa kelemahan yang mengakibatkan ketidakberkesanan. Secara khususnya, (i) Pilihan ciri yang tidak diskriminatif membawa kepada pemisahan antara kelas yang lemah; dan (ii) kerumitan pengelas dipadankan dengan bilangan epoch latihan yang tinggi. Oleh itu, penyelidikan ini bertujuan meneroka pilihan ciri yang paling diskriminatif di samping mencadangkan satu rangka kerja pengkelasan permukaan, identifikasi dan pengesanan kecacatan. Dalam tesis ini, dua rangka kerja dicadangkan; yang pertama adalah untuk pengkelasan dan pengenalan tekstur permukaan sementara yang kedua adalah untuk pengesanan dan pengkelasan kecacatan permukaan keluli.

Kerangka pertama bertujuan menyelesaikan dua tugas. Tugas pertama adalah untuk menghasilkan perwakilan fitur yang paling diskriminatif untuk tekstur permukaan. Ini dicapai melalui kaedah pengekstrakan fitur yang dicadangkan iaitu DST-GLCM, yang merupakan penyepaduan Transformasi Shearlet Diskret (DST) dan Matriks Co-occurrence Aras Kelabu (GLCM) yang menghasilkan vektor fitur padat dan diskriminatif. Satu skema klasifikasi dua peringkat kemudiannya dicadangkan yang menggabungkan keupayaan Mesin Vektor Sokongan (SVM) dan satu teknik cadangan iaitu Latihan Berturut-turut dengan

teknik Rangkaian Neural Buatan Kolektif-Ujian (CTCT-ANN). Peringkat pengkelas SVM mengkelas imej permukaan kepada enam kategori berdasarkan fitur tekstur permukaan. Ini diikuti oleh peringkat CTCT-ANN di mana setiap imej bertekstur permukaan seterusnya dikelaskan lagi kepada subkategori mengikut nilai kekasaran permukaan. Akhirnya, parameter kekasaran permukaan untuk semua imej terkelas dianggarkan.

Rangka kerja kedua bertujuan mengekstrak dan menggabungkan fitur dari bentuk imej permukaan yang berbeza (secara global dan tempatan) ke dalam domain yang berbeza (spatial dan frekuensi). Ini adalah untuk meningkatkan penerangan kandungan imej dan menawarkan variasi perwakilan imej permukaan yang berguna untuk pengesanan kecacatan dan klasifikasi. Fitur global diekstrak daripada imej input menggunakan kaedah DST-GLCM yang dicadangkan pada rangka kerja pertama. Fitur tempatan diekstrak selepas membahagikan setiap imej input kepada empat blok. Kemudian, kaedah GLCM tempatan, Corak Perduaan Tempatan Seragam (ULBP), dan kaedah Fitur Berkualiti Berkelajuan Tinggi (SURF) digunakan untuk mengekstrak fitur dari setiap blok. Semua fitur global dan tempatan yang diekstrak daripada setiap imej digabungkan dalam vektor ciri dimensi tinggi. Saiz vektor ini kemudiannya dikurangkan dan klasifikasi akhir dicapai berdasarkan SVM.

Kedua-dua rangka kerja dinilai menggunakan dua set data permukaan gambar keluli yang berbeza. Rangka kerja pertama menggunakan imej permukaan bahan kerja Tekstur Mesin Kejuruteraan (EMT) yang dihasilkan menggunakan beberapa proses pemesinan. Rangka kerja kedua menggunakan pangkalan data standard Northeastern University (NEU), yang terdiri daripada imej permukaan jalur keluli yang beroperasi dengan pelbagai kecacatan yang berlainan. Keputusan dalam kajian ini menunjukkan peningkatan berbanding dengan kajian yang berkaitan sebelumnya. Ketepatan maksimum yang dicapai dalam pengkelasan permukaan bagi set data EMT adalah sehingga 100%, dengan ralat maksimum dalam pengukuran kekasaran permukaan 0.004 mikrometer. Tambahan lagi, ketepatan maksimum yang dicapai dalam pengesanan kecacatan bagi set data NEU adalah sehingga 99.34%.

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(All Praise Due to the One and Only God, Lord of All Creation)

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I also pray to you oh Allaah, to bless my mother’s soul. This thesis is dedicated to her.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

Fatimah Binti Khalid, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Chairman)

Alfian Bin Abdul Halin, PhD
Senior Lecturer
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

Lili Nurliyana Bt Abdullah, PhD
Associate Professor
Faculty of Computer Science and Information Technology
Universiti Putra Malaysia
(Member)

ROBIAH BINTI YUNUS, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to.

Signature: ____________________________
Name of Chairman of Supervisory Committee: Associate Professor Dr. Fatimah Binti Khalid

Signature: ____________________________
Name of Member of Supervisory Committee: Dr. Alfian Bin Abdul Halin

Signature: ____________________________
Name of Member of Supervisory Committee: Associate Professor Dr. Lili Nurliyana Bt Abdullah

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BPA	Back Propagation Algorithm
CCD	Charge Coupled Device
CMOS	Complementary Metal Oxide Semiconductor
CNN	Convolutional Neural Network
Cr.	Crazing
CTCT	Consecutive Training and Collective Testing
CTCT-ANN	Consecutive Training and Collective Testing - Artificial Neural Networks
DSRM	Design Science Research Methodology
DST	Discrete Shearlet Transform
EMT	Engineering Machined Texture
FN	False Negative
FP	False Positive
GF	Gabor Filter
GLCM	Gray Level Co-occurrence Matrix
GOCM	Gradient-Only Co-occurrence Matrices
In.	Inclusion
IP	Image Processing
KLDA	Kernel-Linear Discriminant Analysis
k-NN	k-Nearest Neighbor
LBP	Local Binary Pattern
LDA	Linear Discriminant Analysis
LIBSVM	Library for Support Vector Machine
MLP	Multilayer Perception
NEU	Northeastern University
NN	Neural Network
NRMSE	Normalized Root Mean Square Error
Pa.	Patches

PC	Personal Computer
PCA	Principle Component Analysis
PS	Pitted Surface
RBF	Radial Basis kernel Function
RGB	Red, Green, and Blue
RS	Rolled-in Scale
Sc.	Scratches
SIFT	Scale-Invariant Feature Transform
SMO	Sequential Minimal Optimization
SRUF	Speeded-Up Robust Features
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
ULBP	Uniform Local Binary Pattern
WT	Wavelet Transform

CHAPTER 1

INTRODUCTION

1.1 Overview

Steel is the material used in a large number of industrial applications. The steel surface and its texture are considered to be the essential components in creating high quality steel strips (Davim 2010). Automatic steel surface inspection systems are the key element of quality control in modern steel industry. The quality of flat steel surface is the most important parameter to ensure the quality of the final product (Neogi et al. 2014). In traditional inspection, surface quality of the flat steel products, which are in coil form, is judged manually by cutting a small sample of a random coil in a batch and inspected by an expert. Typically, in this process the inspected surface is not sufficient to judge the whole produced material (Neogi et al. 2014). The manual inspection process is considered to be speed limited and can be influenced by fatigue, errors, inconsistency and other adverse factors of human's capabilities (Smith 1991). Thus, the manual inspection process is insufficient to guarantee the surface quality of steel products with reasonable degree of confidence and naturally, need for automated surface inspection grew. During the last two decades, automated vision-based inspection techniques of steel surfaces have been found to be very effective to replace the manual-based methods (Xie 2008; Song et al. 2014; Neogi et al. 2014). In manufacturing, machine vision systems are usually applied for inspection of surface defects, sheet metal formed parts, monitoring and control of rolling process and most widely used in tool condition monitoring of conventional machining (Dutta et al. 2014).

Generally, in order to recognize an image accurately in surface texture classification and defect detection problems, different types of features are required to be extracted from the desired image (Tuceryan and Jain 1993). Insufficient features extracted from an image may lead to the shortcomings of the current systems such as low detection rate of various defects (images are classified incorrectly), and high rate of false alarms (images are misclassified as defective) (Kutyniok 2012; Neogi et al. 2014). Image texture can be seen as an image area containing repeated patterns of pixel intensities arranged in some structural way (Baaziz et al. 2010). The spark for this research came from the industry's lack of effective automated visual inspection on the steel profile surfaces. This is due to the complexity of detecting the specific surface texture roughness of the machined steel and the surface defects on the hot-rolled steel strips during manufacturing.

1.2 Problem Statement

i. ***Non-discriminating Properties of Global Descriptors Extracted from Machined Surface Images:*** Machining processes produce unwanted surface features during manufacturing due to several reasons e.g. tool-work system deflection, chatter, cutting tool wear, built-up edge, chip flow, and the thermal effects of the cutting process (Dutta et al. 2014). Since, every machining process is different, these features, which are part of the general surface topology, are unique and characteristic to each machining process. These characteristic surface textures can, thus, be used to identify the type of machining process and determine important information such as the machine tool's kinematics, cutting tool geometries, and machining errors (Patwari et al. 2012). This salient information, about the particular machining process, are vital in meeting the basic goal of any modern manufacturing process, namely, productivity and product quality (Datta et al. 2012). The existing global feature approaches applied to machined steel surface images suffer from certain limitations. For instance the features extracted using Continuous Wavelet Transform (CWT) in Abu-Mahfouz et al. (2017) has limited directional properties to three dimensions only (vertical, horizontal and diagonal), where the surface texture information may lay in multiple directions. This causes loss of the desired texture information extracted from an image which can lead to poor classification accuracy. Moreover, many frameworks such as in Singhka et al. (2016), Chondronasios et al. (2016), Simunovic et al. (2016) and Samtaş et al. (2014) used statistical feature approaches like Gradient-only Co-occurrence Matrices (GOCM), traditional GLCM, or binary image representation. Although these methods are significant for surface texture representation besides implementing those features can be fast and simple, but the effectiveness of such approaches can still be questionable due to the lack of spectral information.

ii. ***Limitation of Learning Algorithms Leading to Poor Texture Roughness Estimation:*** Accurate roughness estimation of machined surface texture is mainly depending on two important steps of discrimination. Firstly, machining-process type classification, secondly texture roughness identification. Recently, Artificial Neural Networks have been playing a significant role in textures classification and recognitions (AlQoud et al. 2016; Wang et al. 2015; Rekha & Shahin 2015; Yuce et al. 2014). Many researches in the past have reported the effectiveness and the good performance of Artificial Neural Networks (ANN) in texture classifications (Rekha & Shahin 2015; Yuce et al. 2014; Singhka et al. 2014) and object recognition (Maria & Balaji 2016; Wang et al. 2015; Nagathan & Mungara 2014). Nevertheless, when large datasets are used, traditional ANNs have not become the best choice for this domain (Nayak et al. 2015), where in order to reach a high performance (accuracy) the network architecture must be more complex and thus number of learning epochs that a network takes in training phase will increase. Many existing researches of surface roughness estimation considered the use of single classification scheme for machined texture. For example Abu-Mahfouz et al. (2017) and Xu et al. (2015) used the Support Vector Machine (SVM) which was able to classify images into its machining classes. However, SVM-based classification methods usually assign images into its corresponding classes without giving any actual numerical output to measure the extent of similarity between the classified image and its corresponding class. As an alternative way Singhka et al. (2016) and Singhka et al. (2014) used ANN in classification, but the discrimination between various texture roughness types requires a complex model of ANN to increase the learning process. Overall, the main issue of the aforesaid single-based approaches lies in the accuracy, where some texture roughness classes can share similar feature description, which causes certain algorithms to detect false alarms. Another issue is regarding model training time, which is a very lengthy process and normally requires tweaking of model parameters.

iii. ***Inaccurate Detection of Surface Defects, and Less Description of Extracted Image Features:*** Hot-rolled steel surface defects are multivariate (e.g. in types, shapes, and orientations) (Zhou et al. 2017; Neogi et al. 2014; Song et al. 2014) so detecting these defects accurately in images requires extracting features in different perspectives (e.g. locally and globally) (Li et al. 2013), as well as in different domains such as spatial and frequency (Xiao et al., 2017). Furthermore, a robust defect detection process is the one which can be relying on extracting the most relevant features from input images in both spatial domain and frequency domain locally and globally. Although spatial domain features extraction methods are significant in detecting the statistical low-level features such as colors, edges, corners, blobs, spots, and size of line segments (El-Gayar & Soliman 2013), nevertheless it miss to capture the multi-orientation and scale information which are extracted by frequency domain feature methods (Baaziz et al. 2010). Thus, depending on feature extraction methods in one single domain means; discarding the features produced by the other domain and those features might be useful in the final discrimination between different defects on the surface image. Consequently, this allows to detect the surface defects under specific detection conditions only, such as obvious defect contours with strong contrast and low noise, at certain scales, or under specific illumination conditions.

1.3 Research Questions

Based on the discussed problem statements, follows are the research questions addressed in this research work.

- What are the best multi-directional feature extraction methods to increase the surface texture classification accuracy of the engineering machined workpiece?
- Is it applicable for one standalone feature to accomplish the above tasks or does it requires combination of multiple features?
- How to extract multiple global and local features from hot-rolled steel images to increase the effectiveness of surface defect detection process?
- Are the SVM, ANN and k-NN classifiers accurate enough for steel surface recognition and discrimination problem?
- Are the existing ANNs techniques suitable for surface roughness identification problem in terms of accuracy, and complexity?
- How to build multi-level classifier based on SVM and ANN for accurate surface discrimination of engineering machined textures.

1.4 Main Aim and Objectives

The main aim of this research is to formulate two effective frameworks for steel surface images that leads to; (i) Classification of the machined surface texture and identification of its roughness value. (ii) Detection and classification of the surface defects in hot-rolled steel strips. To achieve this, the following tasks are to require:

1. To increase the classification accuracy of machined steel surface images by extracting multiple global texture features.
2. To improve the performance of machined steel surface texture roughness estimation by using two-level discrimination scheme.
3. To improve the inspection performance of hot-rolled steel strips surface to produce high-quality steel products with defect-free surfaces.

1.5 Scope of Research

The two steel surface datasets used in this work are; the Engineering Machined Textures (EMT) workpiece surface images, referred as EMT dataset, and the Northeastern University (NEU) standard database (Song & Yan 2016) referred as NEU dataset. The former dataset was collected and prepared typically for the purpose of conducting this research. It is divided into six classes of Turning, Grinding, Lapping, Horizontal-Milling, Vertical-Milling and Shaping. Each class comprises 48 images which are divided into six sub-classes. The images of each sub-class are equal in roughness value but different in machining parameters (i.e. cutting speed, feed rate, and depth of cut). In the latter dataset, 1800 samples are divided equally into six classes of typical surface defects of the hot-rolled steel strips. The six types of defects are collected as; Rolled-in Scale (RS), Patches (Pa), Crazing (Cr), Pitted surface (PS), Inclusion (In) and Scratches (Sc).

1.6 Research Significance

The product quality of steel is mainly controlled by the process of machining. Machined surface finish, is one of the key attributes to determine the product quality which are dependent mainly on the condition of cutting tool wear. Tool wear is dependent on machining conditions, machine tool condition, combination of cutting tool and work piece material, work piece geometry, tool geometry, alignment of work piece and cutting tool, cutting chip condition etc. (Dutta et al. 2014). Thus, it is required to monitor the steel surfaces to control the condition of cutting tool wear to achieve better performance of machining, avoiding machine tool damage and accomplishing the required product quality.

The main significance of this work is the ability to extract the most suitable, effective, and minimized features' set from steel surface images, which leads to higher classification accuracy of different surface texture types, roughness values, and defects. In engineering machined surface texture classification, the surface texture features are extracted and consequently analyzed to help engineers semi- or fully-automatically identify specific machining processes used during production. This allows the important information that characterize the surface roughness finish grade to be acquired such as the machining technique used, the specific tool kinematics, and the identification of possible material defects or anomalies (Dutta et al. 2014). The various surface defects or imperfections produced on the hot-rolled steel during manufacturing processes may not only affect the product appearance, but may also reduce corrosion resistance, wear resistance and fatigue properties (Singhka et al. 2014). The dimensional size of the extracted features can be reduced to the lowest suitable size, which is done by removing redundant and irrelevant features without losing the essential variability present in the original data representation.

Optimizing the architecture model (complexity) of the classifier by performing the training phase in series (successive manner) can also play a major role in increasing the number of true positives (TP), and reducing the training time consumed during classification process.

1.7 Contributions

The work in this thesis presents two main frameworks that led to three salient contributions which are:

1. Introducing a new global features extraction method DST-GLCM that integrates the Discrete Shearlet Transform (DST) and the Gray level Co-occurrence Matrix (GLCM) for machined steel surface texture classification.
2. Proposing a two-level discrimination scheme using SVM and Consecutive Training and Collective Testing-ANN (CTCT-ANN) to improve the machined steel surface texture roughness estimation.
3. Improving the inspection performance of hot-rolled steel surface images by combining the global and local features in both spatial and frequency domains.

1.8 Thesis Outline

This thesis consists of six chapters as illustrated in Figure 1.1. This chapter presents the research motivation, research background, problem statement, main aim and objectives, research questions, overview of research method, scope of research and research significance. The remainder of this thesis is organized as follows: Chapter 2 presents a background and literature review of the related studies in surface image recognition and classification. It introduces the techniques used for steel surface texture classification and roughness identification. This is reviewed along with the existing defect detections and feature extraction techniques.

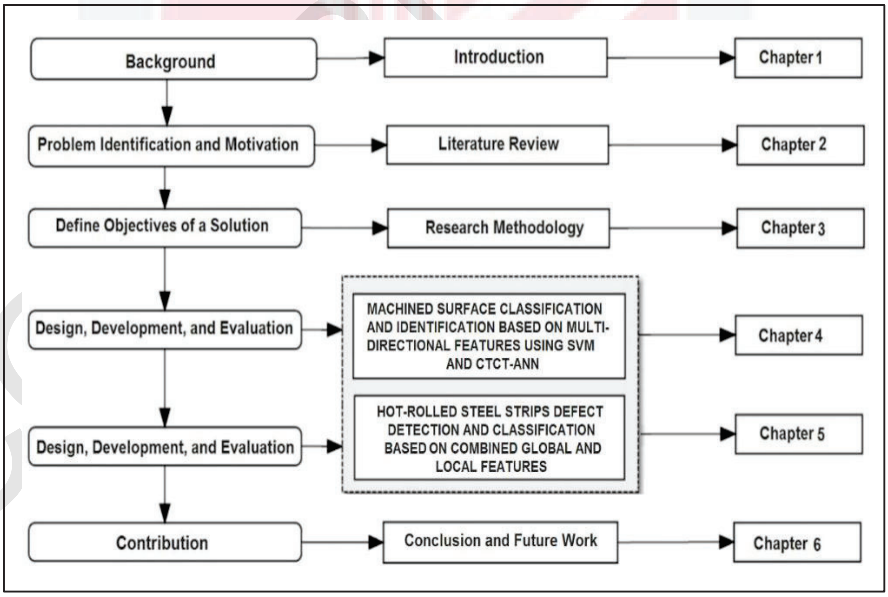

Figure 1.1 : Thesis Outline

Additionally, the chapter presents the techniques and accuracy results of previous researches implemented using the standard database of NEU hot-rolled steel strips surface. Other related works were presented also in order to cover the most relevant work that has been performed recently. Depending on the analysis of the state of art, solutions were proposed and concluded in the chapter. Chapter 3 describes the research methodology used to conduct this study, where the proposed framework's artifact and its evaluation methods are explained and discussed. At the end, a summary of this chapter is presented. Chapter 4 presents the first framework, where the process of acquiring EMT images and converting them into numerical representation is explained. Moreover, the EMT model implementation of the multi-directional features extraction methods is described along with the features reduction step. The multi-level classification and identification scheme based on SVM and CTCT-ANN is also presented and evaluated in this chapter against other existing classifiers. Results achieved, evaluation of the results, and discussions of overall results are also included in the chapter. At the end, a summary of this chapter is presented. Chapter 5 presents the second framework and model implementation of the local and global integrated features for the surface defects detection using the NEU hot-rolled steel strips database. Results achieved, evaluations, and discussions of overall results are also included in the chapter. At the end, a summary of this chapter is presented. Finally, Chapter 6 concludes this thesis with remarks regarding limitations and possible future directions.

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BIODATA OF STUDENT

Mohammed Waleed Ashour was born in Palestine on 19 May 1981. In September 2003, he graduated with a Bachelor of Science (B.Sc.) degree in Computer Engineering from Near East University, Turkish Republic of Northern Cyprus (TRNC). Later, he joined the Arab Academy for Science, Technology and Maritime Transport (in Egypt) to complete his Masters of Science (M.Sc.) degree in Computer Engineering in December 2007.

Mohammed Waleed Ashour was classified as a high achiever since his undergraduate days, where his name was placed on the president's honors list of BSc. and MSc. graduating students. After receiving his Master degree, he was offered several jobs in the higher education sector of different Gulf countries such as UAE and Oman. This is where he learned how to apply the skills and knowledge he gained during his studies to contribute in the development of higher education.

In September 2012, Mohammed Waleed Ashour decided to pursue his doctoral studies by joining the Faculty of Computer Science and Information Technology, Universiti Putra Malaysia (UPM). Research work has occupied a large part of his academic career. To date, he has published eight research papers in different international conferences and journals. His publications have reached up to 27 citations and more than 750 readings on Research Gate. Recently, Mohammed Waleed Ashour was awarded the Doctor of Philosophy (Ph.D.) degree by the UPM senate on 13th December 2018.

LIST OF PUBLICATIONS

Ashour, M.W., Khalid, F., Halin, A.A., Abdullah, L.N. and Darwish, S.H., 2018. Surface Defects Classification of Hot-Rolled Steel Strips Using Multi-directional Shearlet Features. Arabian Journal for Science and Engineering, pp.1-8.

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