CHAPTER 1

INTRODUCTION

The surface finish of a work piece is an issue of concern to the manufacturing industry and the determination of surface roughness of the work piece is a very important task. The surface quality performance has a significant influence on fatigue strength, corrosion resistance, creep life etc. Surface roughness also affects several functional attributes of parts, such as friction, wear, light reflection, heat transmission, ability of distributing and holding a lubricant, coating etc. Therefore, the desired surface finish is usually specified and appropriate processes are applied to maintain the quality. Surface roughness measurement represents an important requirement in many engineering applications. Surface finish is specified as the basic requirement for many produced parts and manufacturing operations in order to satisfy their desired functionality and aesthetics. The surface finish is adopted as a machining process as progressive wear of a cutting tool is a key factor and gradually leading to the deterioration of surface finish. Surface finish refers to the description of the properties of a surface and is a measure of texture, flaws, materials and any applied coatings. Surface texture is often used as a fingerprint of a process and is controlled based on the information obtained from surface texture measurements.

The surface finish is typically expressed in terms of the roughness average $R_a$ or $R_t$. Surface topographic measuring techniques can be divided into three major classes namely profiling, area and microscopy based. Profiling techniques have been reported to be more accurate compared to area techniques. The two conventional ways used for measuring the surface roughness are optical and stylus techniques. The traditional stylus method is the most widely used technique in industry. In this, a precision diamond stylus is drawn through the surface being examined and the perpendicular motion is amplified for further processing. The accuracy of stylus method depends on the radii of diamond tips used. However, when the surface roughness falls below 2.5 μm, the stylus instruments are affected by large system error. The stylus approach has the drawback that it can damage the surface as they require...
direct physical contact and due to line sampling may not represent the real characteristics of the surface. Similarly, the optical technique cannot be used for surface components with roughness values in nanometer range.

To evaluate the surface finish, many assessment techniques for roughness measurement have been proposed. These measurement techniques can be classified into two categories according to whether or not the measuring probe touches the tested work-piece. Traditionally, the commonly used method in an industrial environment is the direct method by means of a profile-meter or a measuring stylus. Even though the stylus instrument is still considered to be the accepted standard for measurement of surface roughness, a non-contact method may present an alternative to allow the surface roughness to be measured rapidly and with an acceptable accuracy. One of the most promising of the non-contact methods in terms of speed and accuracy is the computer vision technique and is the focus of this thesis.

1.1 Machine vision based surface roughness

In this context, Machine vision based surface roughness evaluation has generated a great deal of interest in the technical community have been explored successfully in a variety of tasks such as, sorting and assembling a group of machined parts, checking for microscopic defects in an automotive door panel, etc. The modeling and prediction problems of surface roughness of a work-piece by computer vision have received a great deal of attention. Extensive research has been performed on machine vision applications in manufacturing, because it has the advantage of being non-contact and as well faster than the contact methods. Using Machine Vision, it is possible to evaluate and analyze the area of the surface (the information is extracted using an array of sensors) and enable the user to make application specific intelligent decisions. The advantage of the Machine vision based grabbing of the images on-line is that it does not account for factors like noise and vibrations of machine tool. Machine vision systems need to capture image, extract information using vision sensors and make intelligent decisions.
The sequence of operations - image capture, early processing, region extraction, region labeling, high-level identification and qualitative/quantitative conclusion is characteristic of image understanding and machine vision systems. However, practical surface roughness instruments based on computer vision are still difficult to develop and utilize. It is not yet fully obvious how to accurately acquire engineering measurements of the actual surface roughness of work-pieces using vision data. Conventional techniques use a measure called texture unit, calculated from the gray scale values of the image to the local texture aspect of a given pixel. A wear measurement technique based on the comparison of local surface heights gained from image data is also reported. The differences between the obtained successive surface images can give semi-online information about the amount of wear on asperity level. It combined spacing and amplitude parameters obtained from the gray level profiles to obtain an evaluation parameter. However, it is not quite successful in developing a robust methodology that could be adopted for computer vision based roughness assessment. In general the features calculated from the proposed matrix could be correlated with surface roughness.

Machine Vision and digital image processing for grabbing images of machined surfaces, improving their quality by pre-processing and then analyzed for evaluation of surface finish have been reported with a reasonable success. In the conventional mechanical stylus method used for roughness evaluation, many of the fundamental requirements need to be taken care of during measurement, which includes alignment of component with the stylus pick up movement, tracing length, filter cut off length, etc. The use of Machine Vision for surface roughness estimation does not have such constraints, as in this case only image is used for evaluation and not the component. In this work, estimation of the surface roughness has been done and analyzed using digital images of machined surfaces obtained by a Machine Vision system. The surface finish values ($R_t$) estimated in all such cases using Machine Vision approach are compared with that obtained using conventional stylus method. The grabbed machined image is filtered using a novel Evolvable filter, image features are extracted using wavelet analysis and an artificial neural network (ANN) is trained and tested to arrive at the $R_t$ values using the wavelet feature inputs. The experimental result indicates that the surface roughness could be estimated with a reasonable accuracy using the combined technique of Machine Vision, evolved filtering, wavelet and ANN respectively.
1.2 Roughness measurements

In surface roughness measurements, signals acquired by stylus technique usually undergo filtering to eliminate waviness. Standard filtering cut-off values were introduced to facilitate comparable values of assessing parameters. The common practice in surface roughness evaluation task is based on the computation of signal departure from mean. Acquired data arrays that represent the full evaluation length are usually divided into five sub-arrays of equal number of samples to enable better statistical analysis. These sub-arrays are generally referred to as the sampling length arrays. The most popular technique for roughness measurement is to use surface assessment parameters. The $R_t$ parameter is frequently used and it is the most industrially recognized parameter. However, the $R_t$ parameter is not capable alone to distinguish changes in surfaces, two specimens having a same $R_t$ value may show to possess different surface details. Surface roughness parameters can be grouped into three categories namely: amplitude parameters, spacing parameters, and hybrid parameters.

1.3 Problem statement and solutions

The sequence of operations - image capture, pre-processing, region extraction, region labeling, high level identification, and qualitative/quantitative conclusions are the characteristics of image understanding and machine vision problems. Images processed using computer are digitized first, after which they may be represented by a rectangular matrix with elements corresponding to the brightness at appropriate image locations. Images usually acquired through modern cameras may be contaminated by a variety of noise sources resulting in decreased intensity and in most cases, the types of noise and lighting techniques are also not known apriori. There is a need for design of recognition systems with capability to adapt to changing environments automatically. This requires computing architectures that are less complicated, highly flexible and more cost-effective as compared to the traditional ones, which calculate the coefficients of a general purpose model such as autoregressive, moving average or Autoregressive moving average (ARMA).
A surface can be considered as an image with the Gray levels corresponding to the surface finish. The use of this technique has been reported to extract the hidden periodicities and correlate with the roughness features. Features are extracted from the enhanced images in spatial frequency domain using a two dimensional Fourier Transform and Wavelet Transform. However, the use of Fourier transform yields satisfactory results only for stationary profiles and in many cases, the roughness profiles are non-stationary. It is established in this work that using wavelet transform, improved results for non-stationary profiles also are obtained. An artificial neural network (ANN) is trained using the extracted features (Wavelet transform based) and placed online to estimate $R_t$. The developed model is tested online on images of specimens grabbed by computer vision systems with linearly decreasing intensity. For comparative study, conventional stylus measuring technique is considered and it is established that the proposed machine vision algorithms gives better results and allows complex and fast computations to be performed by dedicated hardware instead of software in a digital computer as hardware units can operate in parallel. This research work can solve partially the unsolved problem of automating the sequence of relevant operations required to solve a specific task.

1.4 Quality of surface finish

The developments in surface finish measurement and standards have always been closely related to the pursuit of quality. The growing influence of surface finish can be traced to dramatic changes in manufacturing specifications and tolerances over the past few decades. The proportion of this tolerance range taken up by surface irregularities has increased from roughly 15 percent to nearly 50 percent today and therefore, the ability to measure and control surface finish is assuming ever greater importance in today's machining operations. Typically, surface finish determines how a part fits and wears, how it reflects light, transmits heat, distributes a lubricant or accepts a coating. On mating parts, though, all surface irregularities have significant and prolonged effect on wear and tear performance, some effects, of course, are more noticeable than others. The classic case is the piston and cylinder in which imperfect surfaces can cause the mating parts to heat up, bind and freeze, possibly even explode. There are also motor driven appliances in which roughness may increase torque and thus require more power to operate. Shafts with poor quality surfaces revolving in bearings will fracture
sooner and undertake less stress than those with appropriately finished surfaces. Thus, the surface finish of machined parts is a very important parameter and needs to be measured with a greater degree of accuracy and preferably using on-line noncontact techniques.

1.5 Image enhancement using EHW filter

In the use of noncontact techniques for machined image acquisition, the process frequently leads to degradation due to different types of noise (for ex: impulse noise) introduced by various inevitable sources. Filtering is a technique used for enhancing the image. Linear filter produce an output pixel that is a linear combination of neighborhood values, but have very less immunity to impulse noise. Thus a variety of smoothing techniques have been developed that are non-linear and median filter is one of the most popular non-linear filter. The median filter suppresses noise by eliminating the local outliers in intensity without any local image blurring. However, this filter is efficient only for a small neighborhood and is highly computation intensive. Alternately, the Centre Weighted Mean (CWM) filter has got a better average performance over the median filter, but is still not acceptable for images that are subject to the extremes of Gaussian noise. The use of Max filter has been proposed in some works, with the advantage of less computation intensive, but they have the drawback that they tend to expand light background regions, and shall tend to reduce the size of objects, or even eradicate small objects.

In this work, a novel Evolvable Hardware (EHW) filter that overcomes the above mentioned limitations, has been designed and implemented for machined image enhancement. The filter has the advantage that it is not model based and hence can filter the noisy image with no apriori information. The EHW filter offsets the constraints of median and CWM filter that the computation is proportional to the area of the window it operates in. The EHW filter operates uniformly on monotonically increasing/decreasing intensity pixels (this feature is absent in median filter). Also, from the hardware implementation point of view, the EHW filter can be implemented with logic blocks and is scalable in architecture. The EHW filter output is compared with conventional machined image enhancement schemes (Karen and Median Filter) for the standard performance metric Peak Signal to Noise Ratio (PSNR).
1.6 Feature extraction using wavelet transforms

In literature, the types of features that are extracted from the enhanced machine image are of varying nature. Some reported works extract machining parameters such as velocity (V), feed (f) and depth of cut (D), and try to correlate them with the surface roughness. However, the degree of correlation is less and result in increased estimation error. Alternately, some works report the use of both machining parameters (V, f and D) and average gray level $G_a$ as choice of feature extraction and correlate them with surface roughness. But, two independent extraction schemes (one based on machining and other based on image processing) imposes additional constraints. Also, only a slight reduction in estimation error is reported. Some works have reported the use of Fourier transforms for feature extraction. But, Fourier transform is well suited for profiles where all the frequency components exist at all times and frequency content remains unchanged with time (stationary). Unfortunately, roughness profiles in many cases are non-stationary (i.e. the frequency components change in time) and in such cases, Fourier transform does not give a good approximation. Hence, a tool that can extract features in the spatial time domain would be more relevant. The wavelet transforms help to give the relevant information that is not obvious in time domain. Therefore, in this research, the use of wavelet transform is explored for extracting surface roughness features.

1.7 Surface roughness estimation using neural network

In estimating the surface roughness using the extracted features, several schemes are reported in the literature. Some works have reported the use of regression technique for surface roughness estimation. However, they are less accurate and any improvement in accuracy shall involve inclusion of large number of approximation terms. Alternately, neural network has been reported for surface roughness estimation. The functionality of a neural network is determined by the combination of the topology (number of layers, number of units per layer, and the interconnection pattern between the layers) and the weights of the connections within the network. The topology is usually held fixed, and the weights are determined by a certain training algorithm. The process of adjusting the weights to make the network learn the relationship between the inputs and targets is called learning, or training.
Different types of learning algorithm have been reported and popular among them are Levenburg-Maquardt and back propagation (BPN) algorithms. In this work, the BPN based neural network is used for estimation of surface roughness.

1.8 Objectives of the work

The objectives of this research work are:

(i) To develop an image enhancement technique, to improve the quality of the images of surfaces by adapting to changes in process variations and adverse conditions in a CIM environment such as contrast reversal and intensity gradients, angular uncertainties, blur caused by changes in depth field, scale changes, partial obliteration or missing features. This is done in this research work by using evolved filters. Initial research involved evolving circuits at a very high primitive gate level and results obtained using this approach showed that evolved circuits were less useful for more demanding commercial applications and is much more complex for nonlinear systems. The task is to seek the optimal logical mapping from all possible mappings. No simple superposition properties exist, and in the most general unconstrained design case, every combination of input variables must be observed a sufficient number of times in order to estimate the conditional probabilities of the output. Extending the system model by adding more parameters leads to a rapid increase in the size of the required training set. This contrasts sharply with the linear problem where it is only required that one estimate the autocorrelation matrix, which is a much smaller set of values than the conditional probabilities. Hence, to overcome this problem a function-level evolution is proposed in this work and domain knowledge is used to select high level computational units, which can be represented directly in the chromosome. Many applications are possible within this context such as noise reduction, shape, character and object recognition, enhancement, restoration, texture classification, spatial and intensity sampling, and rate conversion.
(ii) To apply wavelet transforms and Fourier Transforms independently and extract the relevant features of image texture. The power spectrum can reveal the presence of offset or periodic structures in a data set. The wavelet is a tool in surface texture analysis and can decompose a surface into multi-scale representation in a very efficient way.

(iii) To train a neural network (ANN) and use it for estimating the surface roughness \( R_t \) of components manufactured using processes such as grinding and milling. ANNs have the ability to recognize patterns that are similar, but not identical; it can store information and generalize it. Due to their massive parallelism, ANNs display increased computational power that can be used to deal with complex problems. In this research, back-propagation neural network is used for estimating the surface roughness of the machined surfaces.

(iv) To compare the surface finish obtained using proposed scheme with that using conventional stylus approach.
1.9 Methodology used to implement the work

The methodology used to implement the objectives of this research work is outlined in Figure 1.1.

![Diagram of Methodology](image)

**Figure 1.1 Methodology in the proposed computer vision system for measuring Surface Roughness**

1.10 Scope of the research work

An investigations performed on the use of computer vision technology to evaluate the surface roughness show that practical surface roughness measurements are difficult and the techniques are limited to offline and are also sensitive to lighting and noise. This is mainly due to the reason that the time involved in evaluating the surface roughness is large and also apriori information about the lighting conditions is required. The direct solutions for obtaining high resolution (HR) images are mainly related to sensor manufacturing techniques that attempt to increase the number of pixels per unit area by reducing the pixel size. In addition, there exists a limitation to the reduction of pixel size due to the shot noise problem, which severely degrades the image quality. In this work, to obtain high resolution image from low
cost/resolution sensors, resolution enhancement algorithm that uses evolved filters is implemented. From the enhanced image, features are extracted using the wavelet transform technique and a trained

1.11 Organization of the thesis

Chapter 1 provides an overview on importance of Surface Roughness and quality of Surface Finish. The need, scope and prime objectives of the present work and organization of the thesis are presented in this chapter.

Extensive literature related to EHW filter concepts, performance improvement on Surface Roughness Analysis has been critically reviewed and presented in chapter 2. Summary of review of literature is also furnished.

Chapter 3 presents about the Surface Roughness Analysis and different techniques used to measure Surface Roughness. Detailed discussions on the specifications of Machine Vision System are also incorporated.

Image Enhancement Architecture (EHW Architecture) and Role of Coordinate Logic Filter for noise removal are presented in Chapter 4. Scheme of EHW implementation using evolutionary circuit are discussed in this chapter. Further, the Performance analyses on improvement of PSNR value using EHW on comparing with other filters are also included in this chapter.

Chapter 5 deals with the introduction, characteristics and importance of Wavelet Transforms. Scheme for decomposition at four levels using wavelet is also employed in this chapter. Further the results and performance comparison with complete discussion is concisely provided. Finally, Wavelet based Feature Extracted for Characterization of Surface Roughness is presented in this chapter.
Chapter 6 represents the analysis of Energy Components of the enhanced machined image (both Milling and Grinding) for characterizing the feature with Wavelet transform. Also the performance representing the proposed system is devised and presented. Finally a discussion on the simulation results and the performance comparison is tersely offered for the system.

This Chapter also concludes the thesis by emphasizing the major conjecture of the study. A summary of research contribution and the scope for future studies are also incorporated in this chapter.
CHAPTER 2

LITERATURE REVIEW

Lukas Sekanina [2002] presented image filter design with evolvable hardware. Image recognition is a problem that has to be solved successfully in various industrial applications, namely in automatic traffic sign recognition, car registration number recognition or in the automatic control of the producing line in a factory, where correct and damaged products have to be detected. The quality of recognition algorithm strongly depends on quality of the images coming from a camera since these algorithms are commonly designed for idealized images.

Lukas Sekanina and Stepan Friedl et al., [2005] presented an evolvable combinational unit for FPGAS - DRAFT. A complete hardware implementation of an evolvable combinational unit for FPGAs is presented. In many cases the unit is able to evolve for the required function automatically and autonomously, on the basis of interactions with an environment. It could be classified as a real-time adaptation for some applications then randomly generated various behaviors and interested whether a circuit can be evolved to satisfy the given requirement.

Tomas Martinek and Lukas Sekanina, et al., [2005] proposed an evolvable image filter: experimental evaluation of a complete hardware implementation in FPGA. An efficient image processing algorithms require a certain level of intelligence to correctly interpret and present the input data. To explore the performance of an evolvable image filter that is completely implemented in a Field Programmable Gate Array (FPGA).

A. Sumathi, R. S. D. Wahida Banu, et al., [2006] presented digital filter design using Evolvable Hardware Chip for Image Enhancement. It using evolutionary techniques on a digital filter-system is a possible method for obtaining system adaptability. Providing a high processing speed is therefore often a crucial factor to be considered when implementing real-
time systems. This process is repeated till the desired performance is achieved or particular number of based on primitive gates such as AND-gates and OR-gates generations.

Wei Zhang, Yuanxiang Li, et al., [2008] presented an online evolvable chebyshev filter based on immune genetic algorithm. To serve as the evolutionary algorithm unit and a fast pre-evaluation and bad individual elimination method is employed, which highly increases the speed of evolution and ensures the devices against damage induced by illegal individuals. Due to remarkable advances in recent CPUs and DSPs, applications with analog circuits are rapidly being replaced with digital computing.

Brenda Lin, Mai Irie, et al., [2008] presented the EHW concept and the algorithms used in conjunction with the technology. The development of this field in that each candidate circuit provides some kind of solution to the problem, resides in the environment space. It can be extended to an n-point crossover. Another common recombination technique is called the "uniform crossover". The device is composed of an array of functional units that perform a specific operation, and each unit can be connected in some fashion to another unit.

Uma Rajaram et al., [2009] presented EHW architecture for design of FIR filters for adaptive noise cancellation. It describes a new technique for the design of Finite Impulse Response (FIR) Filter within an Evolvable hardware framework, using genetic algorithm (GA), aimed at noise cancellation. In a reconfigurable Finite Impulse Response (FIR) filter constitutes the backbone of the Adaptive Noise Cancellation. The approach deviates from generic EHW architecture in that it contains two working solutions at any given instant in time, and the more optimized of the two drives the output.

Ch. Ravi Kumar, S.K. Srivathsna proposed EHW architecture for design of adaptive median filter for noise reduction. A new technique for the design of Adaptive Median Filter within an Evolvable hardware framework, aimed at removing the impulse noise from the image and reducing distortion in the image. Therefore, Gaussian and ‘salt and pepper’ noise are added to the image which is processed by the algorithm.
Fan Yang and Michel Paindavoine [2000] proposed a new image filtering technique combining a wavelet transform with a Linear Neural Network. It founds the multiscale Canny-Deriche operator gives the best performance of all models. It evaluates the performance of a pre-processing techniques using wavelet transform applied to face images. In order to evaluate the effect due to pre-processing, they tested the model with different levels of Gaussian random noise added to the test stimulus.

T.V. Vorburger and J. Raja [1990] presented a review of the field, hopefully a fairly inclusive one, and at the same time try to give some insight into the various classes of techniques for measuring surfaces and their uses. On this surface, the lay is in the front-to-back direction. They should add that the words surface roughness, surface roughness, surface texture and surface topography, tend to get used interchangeably.

Irem Y. Tumer, et al., [1996] proposed characteristic measures for the representation of manufactured surface quality. It investigates that yield mathematical measures to analyze the precision of surfaces of manufactured parts. In terms of precision manufacturing, measures provide the potential of detecting and improving surface errors in high-precision product geometry. The average energy is given by the eigenvalues of the covariance matrix.

S.Livens, et al., [1997] proposed Wavelets for Texture Analysis. It includes intuitive properties like roughness, granulation and regularity. To obtain features which reflect scale-dependent properties, one can extract a feature from each sub image separately. The transforms retain localization in both space and frequency, which makes it easy to compute multiscale features locally. Thus rotation invariant features, which preferably still reflect the anisotropy, need to be constructed.

P.Scheunders, et al., [1997] presented the texture analysis based on wavelet transformations is elaborated. It is meant as a practical guideline through some aspects of a wavelet-based texture analysis task. It has even been observed that the responses correspond to Gabor-like functions. The orientation orientational selectivity is even poorer, since it is
represented with just three orientations per scale. It can remedy the coarseness, at the expense of leading to a worse spatial localization.

Jarmo Hurri, et al., [1997] proposed wavelets and natural image statistics. It is an interesting connection between wavelets and statistical properties of real-world images. It is based on statistical analysis of real-world images. Two preprocessing steps were used. (i) low frequency components of the overall images were discarded by subtracting from each sample vector the mean of its components. (ii) to avoid the domination of high variance areas we equalized the local variance in each sample to 1 by dividing each sample by its norm.

Stefan Livens, [1998] proposed a number of image analysis methods as solutions to two applications concerning the characterization of materials. They investigate methods for the automatic characterization of surface corrosion using digital image analysis techniques. It is also interesting as a first successful application of wavelet-based texture analysis in a new application area. A fundamental problem is that the predominant scales that carry the most useful information can differ from one texture to another.

Bruno Josso, et al., [2002] presented frequency normalised wavelet transform for surface roughness analysis and characterization. It means for instance that the deeper a valley, the darker the corresponding pixel, the higher a peak, the brighter the corresponding area in the image. This approach is commonly used to describe the continuous wavelet transform (CWT) for which the mother wavelet can be explicitly expressed. Hence, the wavelet toolbox allows the decomposition of surfaces into form, waviness and roughness components well appreciated by mechanical engineers.

G. K. Kharate, et al., [2005] proposed image compression using wavelet packet tree describes the new approach to construct the best tree on the basis of Shannon entropy. The proposed algorithm provides a good compression performance. The functions are obtained from a single photo type wavelet called the mother wavelet by dilation (scaling) and translation (shifts). These sets are divided into four parts such as approximation, horizontal details, vertical details and diagonal details.
Colin Honess [2006] presented importance of surface finish in the design of stainless steel. The contrast is fine polished finishes with Ra values < 0.5 micron will generally exhibit clean-cut surfaces, with few sites where chloride ions can accumulate. However, it soon became apparent that some of these dull polished finishes had poor corrosion resistance especially when placed at coastal sites.

Sebastian Brol and Wit Grzesik [2007] proposed application of continuous wavelet transform for assessment of surface roughness profile after machining of hardened AISI 52100 steel. It concluded that CWT can be useful for the analysis of the roughness profiles generated by cutting and abrasive machining processes. This situation leads to the conclusion that other tools must be used for proper analysis of non stationary profiles.

S. Kother Mohideen et al., [2008] presented image de-noising using Discrete Wavelet Transform. A de-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. It investigates the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR.

D. Zahn, et al., [1997] proposed a numerical simulation of scattering from rough surfaces using wavelet-based approach. It shows that wavelet basis functions provide substantial reductions in both memory requirements computation time while providing very accurate results. Unfortunately, when using simple pulse or linear expansion and testing functions, it is hard to make the matrix sparse without drastically altering the resulting scattering pattern.

S.Livens, et al., [1997] presented wavelet for texture analysis. It includes intuitive properties like roughness, granulation and regularity. They highlight different aspects of texture, which is a too general and vague concept to encompass is a single description. Multi-resolution techniques intend to transform images into a representation in which both spatial and frequency information is presented.
Kyu-Bock Cho and Joo-Young Oh [1997] proposed presents an overview of an artificial neural network (ANN) based partial discharge (PD) distribution pattern recognition problem to power system application. In this respect, reviews and describes a new novel adaptive pattern recognizing system concerning analysis of measured PD pattern performed on different high voltage apparatus and models of insulating systems using artificial neural network (ANN) and fuzzy principles.

Eko Y. Setiawan and Swapan Chakrabarti [1998] presented neural network-based classifiers have become more popular and advantageous over many conventional classifiers. They investigate a ANN to solve the surface roughness synthesis problem by mapping a single input variable to multiple output variables. Similar to the Ocean surface, the model for the mountain surface is also divided into two components: (i) the mountain base and (ii) the roughness.

Peng Luo, et al., [2000] presented the results of tape surface roughness measurements by both mechanical and magnetic means. The head has three ferrite islands for two write elements and one read element in the center of the head. They observe that the correlation function is symmetric and nearly isotropic. In the mechanical measurement, tape surface roughness correlation length and variance were measured using optical surface analysis. The correlation length of the tape surface roughness was obtained from curve fitting the averaged power spectral density.

R. Saatchi, et al., [2001] presented fuzzy logic cluster analysis of surface roughness waveforms generated using a laser-based system. A laser based system was used to scan the surfaces of 6 steel sheets. The resulting waveforms were pre-processed and then they were represented by a set of feature vectors. The light which is reflected contains information regarding the surface profile of the surface.

Guoliang Fan and Xiang-Gen Xia proposed the wavelet-based texture analysis and synthesis using HMMs. Particularly, we develop a new HMM, called HMT-3S, for statistical
texture characterization in the wavelet domain of the signal energy. The IMM assumes that wavelet coefficients are independent and follow a two-state zero-mean GMM in a scale. It can only characterize the marginal statistics of DWT without considering high-order dependencies of wavelet coefficients.

L Bennaceur Farah, et al., [2006] presented a neural network approach for the inversion of multi-scale roughness parameters and soil moisture. The surface is considered as a superposition of a finite number of one-dimensional Gaussian processes each one having a spatial scale. They have used a multi-scale roughness description is using the wavelet transform and the Mallat algorithm to describe natural surface roughness and investigated the impact of description on radar backscattering through a sensitivity analysis of backscattering coefficient to the multi-scale roughness parameters.

Mashhad, et al., [2006] presented an effective image based surface roughness estimation approach using neural network. An image based surface roughness estimation method was introduced using artificial neural network to accurately establish the relationship between actual surface roughness and 3D texture features of the surface image and consequently effectively estimate surface roughness.

Smriti H. Bhandari and S. M. Deshpande [2007] presented a dual domain approach for surface roughness evaluation. The method uses dual domain of Radon transform and Wavelet transform. It involves the measurement and characterization of surfaces and their relationship to the manufacturing process that generated the part and functional performance measures of the component.

Nigel J. W. Morris, et al., [2007] presented statistics of infrared images. It analyzes the power spectra as well as the marginal and joint wavelet coefficient distributions of datasets of indoor and outdoor images. This analysis has led to significant advances in the fields of image processing and image analysis. If they are not thermal sources, their temperature becomes homogenous through conduction across the object.
Nadir N. Charniya and Sanjay V. Dudul [2007] proposed neural network based sensor for classification of material type and its surface properties. In an experimental prototype was developed which involves bouncing or hopping of the plunger based impact probe freely on the plain surface of an object under test. Surface roughness is a very important parameter for the products of manufacturing industry such as laminating and painting applications, micromachining of polycrystalline silicon films.

Yali Hou, et al., [2008] presented theoretical analysis and experimental evaluation surface morphology integration of grinding and precision finishing. The machining process validity was verified by experimental investigation and theoretical analysis. It indicated that the process is efficient to remove the plastic deformation, to reduce surface roughness and to homogenize ripples. The work surface quality was improved remarkably.

A. Ciccomancini Scogna and M. Schauer [2008] presented performance analysis of stripline surface roughness models. Nevertheless high speed characterization modeling efforts do not often take into account the variations in conductor losses due to copper foil roughness or treatments of copper foil for adhesion. It consists degradation in the stripline performance comparing to the case of model without surface roughness, therefore, in the characterization of high speed transmission lines this effect should be always taken into account.

Guo Feng and Cao Qixin [2004] presented study on color image processing based intelligent fruit sorting system. Fruit area was segmented out from image with an Ohta-color-space based thresholding algorithm: blob algorithm was utilized to remove noises in image: spline-interpolation based algorithm adopted to detect fruit contour. In fruit sorting process, fruit's color ratio, which was calculated with HSI color space, was selected as classification feature.

Chmgjun Liu and Harry Wechsler [1998] proposed a Bayesian framework for face recognition which unifies popular method such as the eigenfaces and Fisherfaces and can generate two novel probabilistic reasoning models (PRM) with enhanced performance. The Bayesian framework first applies Principal Component Analysis (PCA) for dimensionality
reduction with the resulting image representation enjoying noise reduction and enhanced generalization abilities for classification tasks.

E. Rignot and R. Chellappa [1992] presented a bayes classifier for change detection in synthetic aperture radar imagery. Multitemporal SAR observations of natural areas permit monitoring of the characteristics and evolution of structural and electrical properties of natural surfaces as a result of meteorological and phenologic cycles. In this paper, a method is proposed for detecting and quantifying eventual changes in radar backscatter and mapping out ensembles of pixels of spatially and radiometrically homogeneous and similar changes using a Bayes classifier.

Andre B. Soares, et al., [2006] proposed automatic generation of neural networks for image processing. It presented a technique for automatic generation of image processing architectures based on artificial Neural Networks (NN) for real time vision applications in order to reduce the hardware design effort. The generated datapath can be reused with different functions.

R. Caponetto, et al., [1998] proposed Cellular Neural Network Simulator for Image Processing Applications. It presents a cellular neural network software simulator, called SIMUL CN2, for image-processing applications. The software is designed to handle with both black-and-white and 256 gray levels images. All template matrices used, are supposed space invariant with dimension 3x3 or 5x5. The software simulator acts as a development system and an evaluation tool for VLSI chips, currently under study. An automatic optimization tool together with some experimental applications are reported as well.

Edward S. Dunstone [1994] presented a novel neural network architecture for use in image representation and processing. In general methods for using neural networks for image processing have been largely derived from the use of conventional techniques. It is achieved by treating the image as a two-dimensional surface and training a network to learn an approximation to the parametric equation which describes this surface.
Jürgen Becker, et al., [2007] presented new tool support and architectures in adaptive reconfigurable computing. In this contribution the ideas for a novel system approach will be presented in three parts. (i) the hardware and methods providing the multi-adaptivity will be presented. This is the basis for higher level design tools and opens a variety of parameters for adaptivity. In addition the abstraction levels for manipulation the reconfigurable architecture and points to the tool support for novel reconfigurable FPGA architectures from Xilinx are sketched.

Claus, C., et al., [2007] presented using partial-run-time reconfigurable hardware to accelerate video processing in driver assistance systems. This approach is for multi-adaptive reconfigurable systems, which allows a higher degree of freedom for system adaptation. Performing dynamic reconfiguration offers the possibility of on-line routing and placement of communication primitives and functionality in order to optimize the power / performance trade-off in run-time adaptive systems. It can be connected to higher-level design methodologies which used in real applications for driver assistant systems in the automotive domain.

John M. Emmert, et al., [2007] presented most adaptive computing systems use reconfigurable hardware in the form of field programmable gate arrays (FPGAs). For these systems to be fielded in harsh environments where high reliability and availability are a must, the applications running on the FPGAs must tolerate hardware faults that may occur during the lifetime of the system. It presents new fault-tolerant techniques for FPGA logic blocks, developed as part of the roving self-test areas (STARs) approach to online testing, diagnosis, and reconfiguration.

M. Abramovici, et al., [2004] presented on-line BIST and BIST based diagnosis of FPGA logic blocks. During system function mapping, we mask the STAR positions so they are avoided. This way we guarantee the STAR areas are initially available. Subsequently, roving the STARs across the FPGA is implemented by a sequence of pre computed partial reconfigurations and assures that the entire FPGA will eventually be tested.
Guy Gogniat, et al., [2008] presented reconfigurable hardware for high-security/high-performance embedded systems. It focuses on the issues of building secure embedded systems on reconfigurable hardware and proposes a security architecture for embedded systems (SAFES). SAFES leverages the capabilities of reconfigurable hardware to provide efficient and flexible architectural support for security standards and defenses against a range of hardware attacks.

T. Wollinger, et al., [2004] presented another alternative is to consider reconfigurable architecture to implement security primitives instead of using a programmable hardware accelerator. They have demonstrated its very high efficiency but none has focused on the mechanisms required to manage the flexibility of these primitives and to detect attacks.

Brian Moore, et al., [2005] presented design of wireless on-wafer submicron characterization system. A wireless technique for the testing of very large scale ICs and wafers is presented. This test technique uses standard CMOS to achieve wireless parametric testing. This technique has virtually no area overhead, minimal power requirements, and no process or design changes are required. Most compelling is that wafer contact is not required, thereby enabling the in-line process control/monitoring of the manufacture of VLSI wafers or chips.

Ligang Hou, et al., [2006] proposed Neural Network Based VLSI Power Estimation. It forwards a neural network based method on VLSI power estimation. Power estimation technique was a tradeoff between precision and time. Simulation based power estimation gave the most accurate result but time consuming. It used neural network to perform VLSI power estimation.

Chandramouli, et al., [2004] presented multimode power modeling and maximum-likelihood estimation. Linear regression is used to evaluate neural net. Probabilistic results of regression R-value are observed. Analysis shows that unfolded regression R-value sample fit normal distribution. This method can achieve a much faster power estimation result of VLSI on I/O and gate information without simulation and analysis of detail structure and interconnections.
J. Cheatham, et al., [2006] presented a survey of fault tolerant methodologies for FPGAs. It describes some other techniques for tolerating faults in FPGAs. Work on fault tolerance for FPGAs and other memory devices is too extensive to thoroughly cover in this work, so we have limited the scope to reflect a few key efforts that provide a background for the direction our work took.

Sowmya Rani, et al., [2012] proposed content-based image retrieval (CBIR) helps to organize digital picture archives by their visual content. It improves the retrieval accuracy of CBIR systems, it focuses has been shifted from designing sophisticated low-level feature extraction algorithms to reduce the ‘semantic gap’ between the visual features and the richness of human semantics. This paper attempts to provide a comprehensive survey of the recent technical achievements in feature extraction for image retrieval.

Mohamed Rafi, et al., [2011] presented a parametric approach to gait signature extraction for human motion identification. Gait recognition aims essentially to address by identifying people at a distance based on the way they walk i.e., by tracking a number of feature points or gait signatures. It describe a new model-based feature extraction analysis is presented using Hough transform technique that helps to read the essential parameters used to generate gait signatures that automatically extracts and describes human gait for recognition.

M. Tamilarasi, et al., [2012] proposed hierarchical feature cluster based multi-level segmentation for non-proliferative diabetic retinopathy stage diagnosis. To reduce the incidence of blindness and visual impairment due to diabetic retinopathy. Diabetic Retinopathy (DR) disease is a major cause of poor vision loss for the long-standing diabetic patients. It has developed an approach to segment the abnormal regions such as microaneurysms, exudates and hemorrhages in color retinal fundus images.

Rajesh Garg, et al., [2011] proposed image enhancement is one of the most important areas of digital image processing. Histogram modeling techniques can provide a sophisticated method for enhancing the contrast of an image. It is partitioning operation over the input
histogram to chop it into sub-histograms. Then each sub-histogram was subjected to histogram equalization and a specified gray level range was occupied in the enhanced output image.

K. Ratna Babu, et al., [2013] proposed enhancing digital images through artificial bee colony algorithm in combination with morphological operation. Image enhancement is done to improve the quality of images that has been corrupted by some noises or from any other distortions. Mostly, the images contain some noises, thus, the presence of noise produces distortion in an image and so the image will be unattractive.

Gulfishan F. Ahmed, et al., [2011] proposed a study on different image retrieval techniques in image processing. Image enhancement process comprises a set of techniques, which aspire to enhance the visual appearance of an image or to convert the image to a form compatible for analysis by a human or machine. The objective of color enhancement can be either to augment the brightness, or to increase the saturation.

Rajesh Kumar Rai, et al., [2012] proposed underwater image segmentation using clahe enhancement and thresholding. Image enhancement is a process of enhancing the quality of an image by improving its features. For underwater images, three significant image enhancement techniques are utilized: Contrast stretching, Histogram equalization, and Contrast limited adaptive histogram equalization.

Fahim Irfan Alam and Rokan Uddin Faruqui [2011] proposed optimized calculations of haralick texture features. It is simplifying assumptions which are made about the uniform intensities in an image are not reasonable. It optimizes the numerical computation of the Haralick texture features which are used in many different applications, for e.g. in discriminating between different protein structures in microscopic bio-images, recognizing object of interest from satellite images.

B. Naresh Kumar, et al., [2012] proposed an automated 3D segmented and DWT enhanced model for brain MRI. The contributes an edge-based geodesic active contour for the segmentation task by integrating both image edge geometry and voxel statistical homogeneity.
into a novel hybrid geometric–statistical feature to regularize contour convergence and extract complex anatomical structures.

Anna Zawada, et al., [2010] proposed estimation of surface roughness parameter based on machined surface image. The optical method based on the vision system created to acquire an image of the machined surface during the cutting process. The acquired image is analyzed to correlate its parameters with surface parameters.

S. Adamczak, et al., [2010] presented investigating advantages and disadvantages of the analysis of a geometrical surface structure with the use of fourier and wavelet transform. The prediction of machined surface parameters is an important factor in machining centre development. Among various measurement techniques, optical methods are considered suitable for in-process measurement of machined surface roughness.

Harjeetpal Singh and Sakshi Rana [2012] presented image compression hybrid using DCT, DWT and Huffman. Image compression is an essential technology in multimedia and digital communication fields. An image compression technique removes redundant and/or irrelevant information and efficiently encodes what remains. It is necessary to throw away both on redundant information and relevant information to achieve the required compression.

Tiberiu Vesselenyi, et al., [2008] proposed surface roughness image analysis using quasi-fractal characteristics and fuzzy clustering methods. It experiments for surface roughness image acquisition and processing in order to develop an automated roughness control system. This implies the finding of a characteristic roughness parameter (for example Ra) on the bases of information contained in the image of the surface.

Zhongren Wang and Xiaoyu Wang [2012] proposed on-machine measurement of large-scale workpiece based on machine vision. On-machine measurement (OMM) based on machine vision because coordinate measuring machine (CMM) measurement requires significant resources in operating time and cost. It develops an OMM method with a
manipulator and industry camera. It studied on an on-machine calibration method of industry camera based on image sequence.

Latha, J. and N. Devarajan [2012] proposed in-process vision inspection systems for sorting using image processing techniques. Machine vision system is based on digital image processing and is found to be the best sensor detection as its operation is similar to the human eye. The purpose of machine vision is the desire to provide real time machines with visual abilities. Approach: A real time system is developed and is interfaced with the mechanical structure to be used in automobile industry.

R. Suguna and P. Anandhakumar [2011] presented a novel feature extraction technique for texture discrimination using orthogonal polynomial operators. A novel method for extracting texture features from two-dimensional images is presented. The framework is based on a set of operators devised from orthogonal polynomials. Orthogonal polynomial basis for a specific size is generated using Gram-Schmitt process.

Varma M and Zisserman A. [2005] presented a statistical approach to texture classification from single images. The status of a new initiative aimed at developing a versatile framework and image database for empirical evaluation of texture analysis algorithms is presented. Another frequently used approach in texture description is using distributions of quantized filter responses to characterize the texture.

Nafis uddin Khan, et al., [2011] presented image enhancement and de-noising by diffusion based singular value decomposition. For enrichment and denoising of the images having fine edges and homogeneous smooth regions proposed an approach, where a singular value decomposition filtering method has been used on the diffused image subspaces. The prior singular value decomposition based image de-noising method is ineffectual in selecting the optimum threshold parameter for the separation of noise subspace.

Kaganami et al., [2011] presented an optimal technique for improving the contrast of color images based on human visual system. Here, initially the RGB values of each pixel of
the original image have been converted into HSV values. Then, using K-means image segmentation approach, the V component of the original image has been segmented into its dark and bright parts.

B.G. Mertzios and K. Tsirikolias, et al., [1998] presented a number of image processing applications using coordinate logic filters, which execute coordinate logic operations among the pixels of the image. These filters are very efficient in various 1D, 2D, or higher-dimensional digital signal processing applications, such as noise removal, magnification, opening, closing, skeletonization, and coding, as well as in edge detection, feature extraction, and fractal modeling.
CHAPTER 3

SURFACE ROUGHNESS

The quality of components produced is of main concern to the manufacturing industry, which normally refers to dimensional accuracy, form and surface finish. Therefore, the inspection of surface roughness of the work piece is very important to assess the quality of a component, which is normally performed using stylus type devices, which correlate the vertical displacement of a diamond-tipped stylus to the roughness of the surface under investigation. This process is accurate, accepted widely by all the users. But, this method is not suitable for high volume applications as it is time consuming and cumbersome.

Another disadvantage of this stylus method is that it requires direct physical contact with the component and the resolution of this instrument depends mainly on the diameter of the measuring probe tip. With growing demand of industrial automation in manufacturing, machine vision plays an important role in quality inspection and process monitoring. Machine vision for industry has generated a great deal of interest in the technical community over the past several years. Extensive research has been performed on machine vision applications in manufacturing, because it has the advantage of being non-contact and as well faster than the contact methods. Using Machine Vision, it is possible to evaluate and analyse the area of the surface.

In machine vision, surface information is extracted with the help of array of sensors to enable the user to make intelligent decision based on the applications. Machine Vision is many times considered as a subset of artificial intelligence. Machine Vision typically employs a camera, a frame grabber, a digitizer and a processor for inspection tasks where precision, repetition (particularly for mass produced components) and/or high speed are needed.
3.1 Surface roughness parameters with machine vision approach

The non-contact optical methods have attention for the assessment of surface roughness. Most of the methods are based on statistical analysis of grey-level images in the spatial domain. The intensity histograms of the surface image have been utilized to characterize surface roughness and quality. Statistical methods such as co-occurrence matrix approach, the amplitude varying rate statistical approach and run length matrix approach have also been used to compare the texture features of machined surfaces.

![Texture Description process](image)

*Figure 3.1 Texture Description process*
Digital Image libraries are becoming more widely used as more visual information is put in digital form as well as online. To improve human access, however, there must be an effective and precise method for users to search, browse and interact with these collections and to do so in a timely manner. As a result, content-based image retrieval (CBIR) from large image database has been a fast growing research area recently. A simple architecture of a typical CBIR system is shown in Figure 3.2.

![Figure 3.2 Building blocks in texture classification process](image)

Here, two major tasks,

(i) The feature extraction (FE) phase, where a set of feature vectors (FVs) is generated accurately to represent the content of each image in the database. FV is much smaller in size than the original image, typically on the order of hundreds of elements (rather than millions).
To classify the query image by similarity measurement (SM), where a distance between the query images signature obtained by the FV constructed from it and the signature of each image in the signature database. Typically the features used in CBIR systems are low-level image features such as color, texture, and shape.

In this work, the main focus is on the surface images as most of the real world images are measured. Surface image analysis is a topic investigated by researchers in the last few decades. Surface property of an object is reflected in a digital image as a local pattern of intensity variation. The goal of the techniques presented in the literature is to duplicate the ability of the human brain to understand textural characteristics in an efficient way. When a digital image contains regions of distinctly different texture, it is possible to segment the image into its constituent parts based on texture. Sometimes texture is the main property that can be used to distinguish a region from others. Features or rules that characterize texture and the local intensity variations of pixels within a region are known as surface features. A good surface feature must allow one to determine similarities and dissimilarities in intensity variation patterns present in different regions. It is well known that texture of regions cannot be characterized by intensity statistics alone.

When a digital image contains regions of distinctly different surface, is possible to segment the image into its constituent parts based on texture. The feature has to represent statistical as well as structural characteristics of the surface using any mathematical measure or rule. Some of the most popular texture FE methods are based on gray level co-occurrence statistics, gray level run length statistics, probability density functions, fractal dimension (FD), filtering methods like morphological filters, Fourier filters and Gabor filters, random field models, wavelet frames and wavelet packet approaches. The proposed method for extraction of features in this paper is an extension to FD features. Several attempts have been made to characterize texture by its roughness using FD, which is relatively insensitive to illumination and contrast variations. In traditional FD analysis, it is assumed that natural textures exhibit similar roughness over a large number of scales. Hence, a method is proposed which is an extension to the FD concepts where the total scale range is divided into sub-ranges and fractal-based measures are extracted for each
sub-ranges. The idea of considering multiple scale features is extended by considering only a single scale at a time. Hence, in this work features are extracted by considering one scale at a time, to extract all the scale-dependent properties.

Fractal and multi-fractal features requires the use of wavelets. Finding good similarity measures between images based on some feature set is a challenging task. On the one hand, the ultimate goal is to define similarity functions that match with human perception, but, how humans judge the similarity between images is a topic of ongoing research. An important characteristic of texture is directionality. Without this directional information, it may be impossible to distinguish information; it may be impossible to distinguish textures that have no difference otherwise. Perceptual studies identified texture dimensions by conducting experiments that asked observers to group textures according to perceived similarity.

3.2 Combined invariant features

In this section, the various methods like Daubechies wavelet packet decomposition, Gaussian wavelets, Mexican Hat wavelets and the weighted smoothening Gaussian masks are described.

3.2.1 Wavelet packet decomposition

The proposed feature set involves decomposing a texture image with a family of real orthonormal wavelet bases for different levels, computing the wavelet packet coefficients, and computing the energy signatures using the wavelet packet coefficients. Such energy signatures are sorted and combined with other features-like Gaussian and Mexican Hat features for forming the CIF that are used in texture analysis. If an orthonormal wavelet basis has been chosen, the coefficients computed are independent and possess a distinct feature of the original signal. Wavelet packets can be described by the following collection of basis functions:
\[
W_{2n}(2^{p-1}x - l) = \sqrt{2^{l-p}} \sum_{m} h(m - 2l) \sqrt{2^{p}} W_n(2^{p}x - m),
\]
\[
W_{2n+1}(2^{p-1}x - l) = \sqrt{2^{l-p}} \sum_{m} g(m - 2l) \sqrt{2^{p}} W_n(2^{p}x - m),
\]

where, \( p \) is a scale index, \( l \) is a translation index, \( h \) is a low pass filter, \( g \) is a high pass filter with \( g(k) = (-1)^{k}h(1 - k) \). The function \( W_0(x) \) can be identified with the scaling function \( \Phi \) and \( W_1(x) \) with the mother wavelet. The inverse relationship between wavelet packets of different scales can be specified as follows,

\[
\sqrt{2^{p}} W_n(2^{p}x - k) = \sum_{l} h(k - 2l) \sqrt{2^{p-1}} W_{2n}(2^{p-1}x - l) + \sum_{l} g(k - 2l) \sqrt{2^{p-1}} W_{2n+1}(2^{p-1}x - l).
\]

Due to the orthonormal property, the wavelet packet coefficients at different scale and position of a signal \( f(x) \) can be easily computed via,

\[
C_{n,k}^{p} = \sqrt{2^{p}} \int_{-\infty}^{\infty} f(x) W_n(2^{p}x - k) \, dx.
\]

Surface roughness measurement represents an important requirement in many engineering applications. Surface finish is specified as the basic requirement for many produced parts and manufacturing operations in order to satisfy their desired functionality and aesthetics. In manufacturing, the surface finish is adopted as a fingerprint of the machining process, as progressive wear of a cutting tool is a key factor and gradually leading to the deterioration of surface finish. To evaluate the surface finish, many assessment techniques for roughness measurement have been proposed. These measurement techniques can be classified into two categories according to whether or not the measuring probe touches the tested work-piece. Traditionally, the commonly used method in an industrial environment is the direct method by means of a profile-meter or a measuring stylus. Even though the stylus instrument
is still considered to be the accepted standard for measurement of surface roughness, the method has several disadvantages. The non-contact methods may present an alternative to allow the surface roughness to be measured rapidly and with an acceptable accuracy. One of the most promising of the non-contact methods in terms of speed and accuracy is the computer vision technique.

The modeling and prediction problems of surface roughness of a work-piece by computer vision have received a great deal of attention. However, practical surface roughness instruments based on computer vision are still difficult to develop and utilize. It is not yet fully obvious how to accurately acquire engineering measurements of the actual surface roughness of work-pieces using vision data. It measures called texture unit, calculated from the gray scale values of the image, to describe the local texture aspect of a given pixel. However, no real engineering measures could be obtained using the proposed technique. A measurement technique on the comparison of local surface heights gained from image data. They stated that differences between the obtained successive surface images can give semi-online information about the amount of wear on asperity level. It combined spacing and amplitude parameters obtained from the gray level profiles to obtain an evaluation parameter. However, they did not quite succeed in developing a robust methodology that could be adopted for computer vision based roughness assessment.

A gray-level difference matrix for texture analysis that features calculated from the proposed matrix could be correlated with surface roughness. The aim of this paper is to present an evaluation of machine vision data interpretation to acquire roughness parameter measurements and to evaluate the influence of different machining processes on the acquired vision-based roughness parameter values. Twenty different roughness specimens produced by common machining processes namely turning, vertical milling, grinding, reaming, and lapping were experimentally examined in the investigation. Stylus-based measurements of these specimens are acquired and compared to vision-based measurements using amplitude, spacing, and hybrid roughness parameters. Acquired surface data were manipulated using similar data filtering and processing techniques for both stylus and vision data. In addition, a further filtering process based on a moving average technique was also applied to the vision data to
assess the effects of this approach on acquired values of surface parameters. Two models of surface irradiance were employed in the interpretation of the vision data. Ambient lighting was used to minimize the effects of specular reflection. The results of this paper provide an assessment guide of the studied parameters for the utilization of vision-based surface roughness measurement system.

### 3.3 Roughness measurements

In surface roughness measurements, signals acquired by stylus technique usually undergo filtering to eliminate waviness. Standard filtering cut-off values were introduced to facilitate comparable values of assessing parameters. The common practice in surface roughness evaluation task is based on the computation of signal departure from mean. Acquired data arrays that represent the full evaluation length are usually divided into five sub-arrays of equal number of samples to enable better statistical analysis. These sub-arrays are generally referred to as the sampling length arrays. The most popular technique for roughness measurement is to use surface assessment parameters. The Ra parameter is frequently used and it is the most industrially recognized parameter. However, the Ra parameter is not capable alone to distinguish changes in surfaces, two specimens having a same Ra value may show to possess different surface details. Therefore, many other assessment parameters were introduced. Surface roughness parameters can be grouped into three categories namely: amplitude parameters, spacing parameters, and hybrid parameters. In this work, the three types of different roughness assessment parameters are adopted and used to achieve the goal.

#### 3.3.1 Adopted surface roughness parameters

The adopted surface roughness parameters are computed from the data array denoted by $G(n)$, where $n = 1, 2, 3, \ldots, N$. $G$ is the departure from the reference mean of the evaluation length profile data. However, to enable better statistical analysis of acquired data, the profile data array is divided into five sub-arrays (frequently referred to in the literature as the sampling length sub-arrays) denoted by $g_i(m)$, where the subscript $(i)$ presents the sub-array
sequence number and \((m)\) is the sample number in the sub-array thus \(m = 1,2,3,\ldots,N/5\). These parameters are shown in Table 1.

**Table 1 The adopted surface roughness parameters**

<table>
<thead>
<tr>
<th>Parameter Description</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average height departure parameter ((R_a))</td>
<td>(R_a = \frac{1}{N} \sum_{n=1}^{N}</td>
</tr>
<tr>
<td>Root mean square parameter ((R_q))</td>
<td>(R_q = \sqrt{\frac{1}{N} \sum_{n=1}^{N} G^2(n)})</td>
</tr>
<tr>
<td>Maximum peak to valley set of parameters</td>
<td>(R_d = \max_{m=1,2,3,\ldots,N/5} (g_i(m)) - \min_{m=1,2,3,\ldots,N/5} (g_i(m)))</td>
</tr>
<tr>
<td>Maximum valley depth set of parameters</td>
<td>(R_v = \max_{n=1,2,3,\ldots,N} (G(n)) - \min_{n=1,2,3,\ldots,N} (G(n)))</td>
</tr>
<tr>
<td>The sum of the valley depth set of parameters</td>
<td>(R_{v\text{sum}} = \frac{1}{5} \sum_{i=1}^{5} R_{v\text{max}}(i))</td>
</tr>
<tr>
<td>Maximum peak height set of parameters</td>
<td>(R_p = \max_{m=1,2,3,\ldots,N/5} (g_i(m) - C))</td>
</tr>
<tr>
<td>Skewness parameter ((R_{sk}))</td>
<td>(R_{sk} = \frac{1}{R_q} \times \frac{1}{N} \sum_{n=1}^{N} G^3(n))</td>
</tr>
<tr>
<td>Kurtosis parameter ((R_{ku}))</td>
<td>(R_{ku} = \frac{1}{R_q^4} \times \frac{1}{N} \sum_{n=1}^{N} G^4(n))</td>
</tr>
<tr>
<td>Mean of spacing parameter ((R_{vm}))</td>
<td>(R_{vm} = \frac{1}{J} \sum_{j=1}^{J} S_j)</td>
</tr>
<tr>
<td>RMS–slope hybrid parameter (R_{Aq})</td>
<td>(R_{Aq} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (\theta(n) - \bar{\theta})^2})</td>
</tr>
</tbody>
</table>

where \(S_j\) presents the spacing distance between each adjacent local peaks and \(J + 1\) is the total number of acquired local peaks.

\(\bar{\theta} = \frac{1}{N} \sum_{n=1}^{N} \theta(n)\)

and \(\theta = \frac{G(n) - G(n+1)}{\text{sampling rate}}\)
3.4 Image data implementation for surface roughness measurements

Surface roughness measurements are computed using data acquired from the employed stylus-based system. The ratio of the standard deviation to the mean value of Ra for each specimen is also shown in Table 2 for completeness.

Table 2 The specimens used in the experimental work

<table>
<thead>
<tr>
<th>Specimen code</th>
<th>Machining type of specimen surface</th>
<th>Average stylus-based $R_a$ ($\mu$m) (cutoff used is 0.8 mm)</th>
<th>Percentage ratio of (standard deviation to mean value) of the resulting $R_a$ values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tum 1</td>
<td>Turning</td>
<td>7.303</td>
<td>1.14</td>
</tr>
<tr>
<td>Tum 2</td>
<td>Turning</td>
<td>3.546</td>
<td>2.65</td>
</tr>
<tr>
<td>Tum 3</td>
<td>Turning</td>
<td>1.942</td>
<td>1.92</td>
</tr>
<tr>
<td>Tum 4</td>
<td>Turning</td>
<td>0.908</td>
<td>5.82</td>
</tr>
<tr>
<td>V-mill 1</td>
<td>Vertical milling</td>
<td>8.037</td>
<td>5.47</td>
</tr>
<tr>
<td>V-mill 2</td>
<td>Vertical milling</td>
<td>3.331</td>
<td>2.09</td>
</tr>
<tr>
<td>V-mill 3</td>
<td>Vertical milling</td>
<td>1.785</td>
<td>3.84</td>
</tr>
<tr>
<td>V-mill 4</td>
<td>Vertical milling</td>
<td>0.588</td>
<td>7.58</td>
</tr>
<tr>
<td>Grind 1</td>
<td>Surface grinding</td>
<td>1.679</td>
<td>3.90</td>
</tr>
<tr>
<td>Grind 2</td>
<td>Surface grinding</td>
<td>0.815</td>
<td>12.24</td>
</tr>
<tr>
<td>Grind 3</td>
<td>Surface grinding</td>
<td>0.435</td>
<td>16.91</td>
</tr>
<tr>
<td>Grind 4</td>
<td>Surface grinding</td>
<td>0.260</td>
<td>7.66</td>
</tr>
<tr>
<td>Grind 5</td>
<td>Surface grinding</td>
<td>0.118</td>
<td>13.56</td>
</tr>
<tr>
<td>Grind 6</td>
<td>Surface grinding</td>
<td>0.068</td>
<td>4.36</td>
</tr>
<tr>
<td>Rem 1</td>
<td>Reaming</td>
<td>1.953</td>
<td>5.72</td>
</tr>
<tr>
<td>Rem 2</td>
<td>Reaming</td>
<td>1.266</td>
<td>9.19</td>
</tr>
<tr>
<td>Rem 3</td>
<td>Reaming</td>
<td>0.523</td>
<td>5.61</td>
</tr>
<tr>
<td>Lap 1</td>
<td>Lapping</td>
<td>0.227</td>
<td>5.74</td>
</tr>
<tr>
<td>Lap 2</td>
<td>Lapping</td>
<td>0.138</td>
<td>23.8</td>
</tr>
<tr>
<td>Lap 3</td>
<td>Lapping</td>
<td>0.078</td>
<td>11.49</td>
</tr>
</tbody>
</table>

The diffuse model, it is assumed that the surface fully complies with Lambert’s law; hence the image intensities (z) could be employed to compute the surface normal vectors. These are used thereafter to acquire the surface profile. The difference of surface normal angles between each two successive points in an image line (dba(n)) could be obtained by employing the image array of the normalized gray scale values ($a_{Norm}$),

$$\delta \beta_{a(n)} = \cos^{-1}(a_{Norm}(n)) - \cos^{-1}(a_{Norm}(n + 1)).$$

(4)
Therefore, the acquired dba(n) is then implemented to re-construct the surface profile using ordinary trigonometric relationships and scaled to the actual amplitudes of the specimen profiles using the corresponding k ratio. Fig. 3.3 presents a flow chart of the proposed methodology to compute the vision-based roughness parameters based on image data re-scaling. It is worth noting that the adopted filtering technique was based on 0.8 mm cut-off value and were maintained identical for both stylus and vision data to enable comparable results.
Figure 3.3 A flow chart of the proposed system of vision-based computation of roughness parameters by employing stylus-based calibration methodology.
The ITC with double filter model investigated to assess its impact on the vision-based computed roughness parameters and whether acquired results will encourage or discourage using such filtering technique in future applications. Vision-based set of data implementing the diffuse model and filtered using the same filtering technique as the stylus-based data, i.e. 0.8 mm cut-off value.

Computer images of the specimens are acquired using the employed vision system with a resolution of 12.5 μm/pixel. An equivalent sampling resolution was used to acquire the stylus based data, i.e. 80 samples per millimeter. Computation of \( R_a \) parameter using vision data were achieved by application of the proposed methodology shown in the flow chart of Fig. 3.3.

### 3.5 Surface roughness estimation

The surface roughness parameter used throughout in this study is the average surface roughness (Ra) as it is the most widely used surface finish parameter by researchers and in industry as well. It is the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value measured, that is

\[
R_a = \left( \frac{\sum_{i=1}^{n} |y_i|}{n} \right)
\]

where, \( y_i \) is the height of roughness irregularities from the mean value and \( n \) is the number of sampling data. In this study, a feature of the surface image, called the arithmetic average of the grey level \( G_a \), is used to predict the actual surface roughness of the workpiece. The arithmetic average of the grey level \( G_a \) can be expressed as,

\[
G_a = \left( \frac{\sum |g_1 - g_m| + |g_2 - g_m| + \cdots + |g_n - g_m|}{n} \right)
\]

where, \( g_1, g_2, g_3, \ldots, g_n \) are the gray level values of a surface image along one line and \( g_m \) is the mean of the grey values and this can be determined as

\[
g_m = \left( \frac{\sum (g_1 + g_2 + \cdots + g_n)}{n} \right)
\]
The grey level average (Ga) has been calculated for all the surfaces after the images of the surface were captured. These Ga values have been calibrated with the respective Ra values measured using a stylus profilometer.

### Table 3 Machining parameters used for grinding and the roughness values

<table>
<thead>
<tr>
<th>Speed (rpm)</th>
<th>Depth of cut (doc) (µm)</th>
<th>Ga, optical parameter</th>
<th>Ra (µm), stylus parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>1801</td>
<td>50</td>
<td>15.09</td>
<td>0.51</td>
</tr>
<tr>
<td>2204</td>
<td>50</td>
<td>10.54</td>
<td>0.49</td>
</tr>
<tr>
<td>2593</td>
<td>50</td>
<td>9.03</td>
<td>0.48</td>
</tr>
<tr>
<td>1809</td>
<td>30</td>
<td>12.17</td>
<td>0.52</td>
</tr>
<tr>
<td>1501</td>
<td>30</td>
<td>14.94</td>
<td>0.53</td>
</tr>
<tr>
<td>2000</td>
<td>30</td>
<td>8.73</td>
<td>0.49</td>
</tr>
<tr>
<td>1800</td>
<td>80</td>
<td>15.93</td>
<td>0.51</td>
</tr>
<tr>
<td>2202</td>
<td>80</td>
<td>14.33</td>
<td>0.48</td>
</tr>
<tr>
<td>2593</td>
<td>80</td>
<td>9.13</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Multiple linear regression equations have been developed for each of the machining processes based upon the data presented in Tables 1–3.

They are as follows:

(a) Grinding:

\[
R_a = 0.52 - (1.9 \times 10^{-5}) \text{ speed} - (0.00044) \text{ doc} + (0.003322) \text{ Ga}
\]

(b) Milling:

\[
R_a = -0.97 + (0.0003) \text{ speed} - (0.00694) \text{ feed} + (0.415) \text{ doc} + (0.1985) \text{ Ga}
\]

(b) Shaping:

\[
R_a = -7.182 + (0.0683) \text{ speed} + (11.44) \text{ feed} + (5.61) \text{ doc} + (0.328) \text{ Ga}
\]
3.6 Magnification and surface roughness

The roughness evaluation of surfaces using machine vision involved correlating the spectra of such surfaces to the roughness values and these have been shown to follow power law behavior. Profile of such surfaces were shown to be self-affined which implies that when magnified, increasing details of roughness emerge and appear similar to the original profile.

### Table 4 Machining parameters used for milling and the roughness values

<table>
<thead>
<tr>
<th>Speed (rpm)</th>
<th>Feed (mm/min)</th>
<th>Depth of cut (mm)</th>
<th>$G_a$, optical parameter</th>
<th>$R_a$ (µm), stylus parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>125</td>
<td>22.4</td>
<td>0.5</td>
<td>15.61</td>
<td>2.17</td>
</tr>
<tr>
<td>250</td>
<td>22.4</td>
<td>0.5</td>
<td>19.35</td>
<td>2.94</td>
</tr>
<tr>
<td>90</td>
<td>22.4</td>
<td>0.5</td>
<td>21.30</td>
<td>3.51</td>
</tr>
<tr>
<td>90</td>
<td>45</td>
<td>0.5</td>
<td>18.23</td>
<td>2.69</td>
</tr>
<tr>
<td>125</td>
<td>45</td>
<td>0.5</td>
<td>28.89</td>
<td>4.45</td>
</tr>
<tr>
<td>180</td>
<td>45</td>
<td>0.5</td>
<td>16.99</td>
<td>2.44</td>
</tr>
<tr>
<td>90</td>
<td>45</td>
<td>1</td>
<td>27.16</td>
<td>4.75</td>
</tr>
<tr>
<td>125</td>
<td>45</td>
<td>1</td>
<td>19.04</td>
<td>3.02</td>
</tr>
<tr>
<td>63</td>
<td>45</td>
<td>1</td>
<td>17.71</td>
<td>2.46</td>
</tr>
<tr>
<td>63</td>
<td>22.4</td>
<td>1</td>
<td>21.36</td>
<td>3.41</td>
</tr>
<tr>
<td>90</td>
<td>22.4</td>
<td>1</td>
<td>25.51</td>
<td>4.41</td>
</tr>
<tr>
<td>125</td>
<td>22.4</td>
<td>1</td>
<td>26.46</td>
<td>4.65</td>
</tr>
</tbody>
</table>

### Table 5 Machining parameters used for shaping and the roughness values

<table>
<thead>
<tr>
<th>Speed (rpm)</th>
<th>Feed (mm/stroke)</th>
<th>Depth of cut (mm)</th>
<th>$G_a$, optical parameter</th>
<th>$R_a$ (µm), stylus parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>0.2</td>
<td>0.5</td>
<td>22.31</td>
<td>19.06</td>
</tr>
<tr>
<td>18</td>
<td>0.2</td>
<td>0.5</td>
<td>17.21</td>
<td>19.83</td>
</tr>
<tr>
<td>24</td>
<td>0.2</td>
<td>0.5</td>
<td>21.07</td>
<td>21.34</td>
</tr>
<tr>
<td>18</td>
<td>0.6</td>
<td>0.5</td>
<td>24.95</td>
<td>24.58</td>
</tr>
<tr>
<td>24</td>
<td>0.6</td>
<td>0.5</td>
<td>28.31</td>
<td>26.55</td>
</tr>
<tr>
<td>18</td>
<td>0.2</td>
<td>1</td>
<td>14.86</td>
<td>20.38</td>
</tr>
<tr>
<td>18</td>
<td>0.4</td>
<td>1</td>
<td>19.1</td>
<td>26.63</td>
</tr>
<tr>
<td>12</td>
<td>0.4</td>
<td>1</td>
<td>18.92</td>
<td>25.31</td>
</tr>
<tr>
<td>18</td>
<td>0.4</td>
<td>0.5</td>
<td>29.62</td>
<td>27.74</td>
</tr>
<tr>
<td>24</td>
<td>0.4</td>
<td>0.5</td>
<td>19.61</td>
<td>23.44</td>
</tr>
<tr>
<td>12</td>
<td>0.2</td>
<td>1</td>
<td>18.7</td>
<td>21.36</td>
</tr>
<tr>
<td>24</td>
<td>0.2</td>
<td>1</td>
<td>20.44</td>
<td>22.14</td>
</tr>
<tr>
<td>24</td>
<td>0.4</td>
<td>1</td>
<td>17.23</td>
<td>24.72</td>
</tr>
</tbody>
</table>
An attempt has been made to correlate the grey level average ($G_a$) values obtained from the images with their respective surface roughness and study the behavior of such a correlation at various degrees of image magnification for the three machining operations. The feature of the image extracted and a correlation between $G_a$ and surface roughness $R_a$ was established on the basis of data based on the values of correlation coefficient so obtained, plots have been drawn between the magnification factor and correlation coefficient from the data machining processes.

3.7 Statistical modeling of surface roughness

3.7.1 Introduction

Surface roughness, is a measure of surface quality is one of the specified requirements in a machining process. The machine vision applications have been carried out many researches in industries, as they have the benefit of being non-contact and speedy process than contact methods. In machine vision, is possible to analyze and determine the area of the surface, in which machine vision information will assist sensors to make intelligent decision on the applications. In this work, surface roughness estimation has been done by machine vision system. The extraction of features for the enhanced images is in spatial frequency domain done with the facilitate of Fourier Transform and Wavelet Transform. A neural network (NN) is trained with feature extracted values as input acquired from wavelet transform and examined to obtain $R_t$ as output. The estimated surface roughness parameter ($R_t$) based on NN, which is compared with the $R_t$ values from Stylus method is obtained as results. Machine vision based surface roughness evaluation has generate a deal of interest in the technical community have been explored in a variety of tasks such as, sorting and assembling a group of machined parts, checking for microscopic defects in an automotive door panel, etc. The modeling and prediction problems of surface roughness of a work-piece by computer vision have received a great deal of attention. Extensive research has been performed on machine vision applications in manufacturing, because it has the advantage of being non-
contact and as well faster than the contact methods. Using Machine Vision, it is possible to evaluate and analyze the area of the surface (the information is extracted using an array of sensors) and enable the user to make application specific intelligent decisions. The advantages of the machine vision based grabbing of the images on – line is that it does not account for factors like noise and vibrations of machine tool. Machine vision system need to capture image, extract information using vision sensors and make intelligent decisions.

The sequence of operations-image capture, early processing, region extraction, region labeling, high-level identification and qualitative/quantitative conclusion is characteristic of image understanding and machine vision systems. However, practical surface roughness instruments based on computer vision are still difficult to develop and utilize. It is not yet fully obvious how to accurately acquire engineering measurements of the actual surface roughness of work-pieces using vision data. Conventional techniques use a measure called texture unit, calculated from the gray scale values of the image to the local texture aspect of a given pixel. The differences between the obtained successive surface images can give semi-online information about the amount of wear on asperity level. It combined spacing and amplitude parameters obtained from the gray level profiles to obtain an evaluation parameter. However, it is not quite successful in developing a robust methodology that could be adopted for computer vision based roughness assessment. In general the features calculated from the proposed matrix could be correlated with surface roughness.

Machine Vision and digital image processing for grabbing images of machined surfaces, improving their quality by pre-processing and then analyzed for evaluation of surface finish with a reasonable success. In the conventional mechanical stylus method used for roughness evaluation, many of the fundamental requirements need to be taken care of during measurement, which includes alignment of component with the stylus pick up movement, tracing length, filter cut off length, etc. The use of machine vision for surface roughness estimation does not have such constraints, as in this case only image is used for evaluation and not the component. In this work, estimation of the surface roughness has been done analyzed using digital images of machined surfaces obtained by a Machine Vision system. The surface
finish values ($R_t$) estimated in all such cases using Machine Vision approach are compared with that obtained using conventional stylus method. The grabbed machined image is filtered using a novel Evolvable filter, image features are extracted using wavelet analysis and an artificial neural network (ANN) is trained and tested to arrive at the $R_t$ values using the wavelet feature inputs. The experimental result indicates that the surface roughness could be estimated with a reasonable accuracy using the combined technique of Machine Vision, evolved filtering, wavelet and ANN respectively.

A comparison of surface finish attained using proposed scheme with that of using classical and conventional stylus approach Figure 3.4.

Fig. 3.4 Surface Roughness Study
3.7.2 Factors affecting surface Roughness

The surface finish is dependent usually on the following machining parameters: (i) Type of cutting tool (ii) speed of the lathe. Accordingly, the surface roughness can be modeled as

\[ S_R = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon \]  

... (3.1)  
(or)

\[ S_R = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \epsilon \]  

... (3.2)

where, \( x_1 \) is the lathe speed in rpm, \( x_2 \) is the type of cutting tool and is a discrete variable. The dependency of surface roughness on \( x_1 \) and \( x_2 \) is shown in Figure 3.5. Similarly for eqn. (3.2) the variation is shown in Figure 3.6. From Figure 3.5 and Figure 3.6, can be inferred that surface roughness is linearly related to lathe speed and \( \beta_2 \) alters the intercept and \( \beta_3 \) alters the slope.

Fig. 3.5  Surface roughness Vs \( x_1 \) & \( x_2 \)

Fig. 3.6  Surface roughness Vs \( x_1; x_2 \) & \( x_1 x_2 \)
3.7.3 ANOVA for surface roughness model

The analysis of variance for the model of eqn. (3.1) is done and results are shown in Table 6. This analysis is done to determine whether the tool type has an effect on surface roughness. The advantage of the indicator variable scheme is (i) only one regression model must be fit and (ii) more degrees of freedom error is available. Alternately, separate regression model can be fit to the data for each $x_2$. However, the indicator variable approach is advantageous. Thus, two different regression model ($\beta_2 \neq 0; \beta_3 \neq 0$) are required to adequately model the surface roughness dependency on machining parameters. Similarly, the surface roughness variation with variation of carbon material properties is shown in Figure 3.7.

![Fig. 3.7 Surface roughness variation with variation of carbon material properties](image)

Fig. 3.7 Surface roughness variation with variation of carbon material properties
3.7.4 ANOVA Based Multi Factor Analysis of surface Roughness

The effect of tool and carbon material property on surface roughness is discussed. However, in actual practice, additional factors such as feed rate, depth of cut and tool angle are also important. The joint effect of the multiple factors on surface roughness is analyzed factorial methods and the results are shown in Figure 3.8.

![Graph showing variation of surface roughness with respect to F, DoC, and Tool Angle.](image)

**Fig. 3.8 Variation of surface Roughness w.r.t. F, DoC and Tool Angle**

**Table 6 Significance tests for assessing surface roughness effect**

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Remarks</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0 : \beta_1 = \beta_2 = 0$</td>
<td>P-Value very small</td>
<td>Rejected</td>
</tr>
<tr>
<td>$H_0 : \beta_2 = 0$</td>
<td>P-Value very small</td>
<td>Rejected</td>
</tr>
<tr>
<td>$H_0 : \beta_2 \neq 0$</td>
<td></td>
<td>Accept</td>
</tr>
<tr>
<td>$H_0 : \beta_2, \beta_3 \neq 0$</td>
<td></td>
<td>Accept</td>
</tr>
</tbody>
</table>
Table 7 Energy Details

<table>
<thead>
<tr>
<th>Ea</th>
<th>Et</th>
<th>Eh</th>
<th>Ev</th>
<th>Ed</th>
<th>Ed</th>
</tr>
</thead>
<tbody>
<tr>
<td>99.028</td>
<td>0.0396</td>
<td>0.1714</td>
<td>0.4482</td>
<td>0.3122</td>
<td>0.3122</td>
</tr>
<tr>
<td>99.008</td>
<td>0.0204</td>
<td>0.1183</td>
<td>0.3862</td>
<td>0.4663</td>
<td></td>
</tr>
<tr>
<td>97.741</td>
<td>0.0272</td>
<td>0.2686</td>
<td>0.6214</td>
<td>1.3414</td>
<td></td>
</tr>
</tbody>
</table>

Figure 3.9 can be inferred that surface roughness is most affected by the factors A, B, BC for a threshold of 3.0. The geometric view of the factors interaction effect on the surface roughness is shown in Figure 3.10. Each corner represents the standard deviation of the influencing factor.

Fig 3.9 Self and combined effects on surface Roughness

Fig. 3.10 Maximal Interaction effects with threshold = 3.0

A = 3.375; B = 1.625; C = 0.875;
AB =1.375; AC = 0.125; BC = 0.625; ABC = 1.125;
3.8 Surface roughness factors interaction effect

Surface metrology is a vital and demanding area of research in industries, dealing with real time applications. It has become mandatory for production to consider the quality and performance testing relating to the tool surface. In several engineering applications surface finish plays a key role. Good quality machined components significantly improves fatigue strength, corrosion resistance, creep life which depends entirely on surface of the part. Friction, light reflection, heat transmission, wear and tear, ability of distributing and holding a lubricant, coating are the outstanding parameters affected by surface roughness. Thus, surface finish must be specified and suitable processes are required to uphold the quality and assess the quality of a component of the work piece.

The terms $R_a$ is used to express the average roughness in measuring surface finish. The three major Surface topographic measuring techniques are area, profiling and microscopy based. Profiling techniques are reported to be more accurate compared to area and microscopy techniques. The two straight ways used for measuring the surface roughness are stylus and optical techniques.

The stylus is the most widely used technique in industry. Radius of diamond tip is the base to approximate the accuracy of stylus method. When the surface roughness is identified as below 2.5 μm, the stylus instruments are affected by system error. The stylus approach has the problem that spoils the surface as they need direct physical contact. Similarly, the optical technique cannot be used for surface components whenever roughness values fall in nanometer range.

This led to machine vision based surface roughness evaluation in various tasks such as, microscopic defects, sorting and assembling of machined parts. Machine vision can also be referred as computer vision or artificial vision. Machine vision is found to be less contact and faster, thus, many researchers have performed on machine vision applications in manufacturing based industries. Machine Vision can evaluate and analyze the area of the surface and helps the user to make intelligent decisions. The results obtained are validated by
plotting the correlation graph between stylus measured (conventional method) $R_t$ and vision measured (proposed) $R_t$ for both the FT and WT techniques for milled components is shown in Figure 3.11.

Fig. 3.11 Geometric view of the factors interaction effect on the surface roughness
CHAPTER 4

MACHINED IMAGE ENHANCEMENT USING EHW FILTER

4.1 Evolvable Hardware

Evolvable Hardware (EHW) is a hardware whose architecture, structure and functions change dynamically and autonomously in order to improve its performance in performing certain tasks. The emergence of this field has been influenced profoundly by the progress in reconfigurable hardware and evolutionary computation. It is impossible to change the hardware's structure and function once it is made. However, most real world problems are not fixed. EHW provides an ideal approach- making hardware adapts the hardware structure to problem dynamically. There are differing views on the definition of EHW. Some regard it as the application of evolutionary techniques to electronic hardware design. Some regard it as hardware capable of online adaptation by reconfiguring its architecture dynamically and autonomously. The former emphasizes evolutionary computation techniques as potential design tools, while the latter emphasizes adaptation of hardware. There are two major aspects to EHW,

(i) simulated evolution and
(ii) electronic hardware

There is no uniform answer as to which type of evolutionary algorithm would be the best for EHW. The electronic hardware used in EHW can be digital, analog or hybrid circuits. One of the advantages of evolutionary algorithms is that they impose very few constraints on the type of circuits used in EHW.

An initial population of architecture bits encoded as chromosomes is generated either randomly or heuristically. They are then downloaded into FPGAs for fitness evaluation. Some EHW has only one set of FPGA hardware that will be used to evaluate the fitness of every chromosome sequentially. The fitness of an FPGA, which is normally equivalent to the
fitness of its chromosome, is evaluated through its interaction with the environment. Such fitness is then used to select parent chromosomes for further reproduction and genetic operation. Crossover and Mutation are often used to generate offspring chromosomes from the parents. These offspring will then replace their parents according to certain replacement strategies. The Figure 4.1 shows the major steps in an evolutionary cycle of EHW. Some replacement strategies may retain a parent and discard its offspring. A new generation of chromosomes is formed after replacement.

![Fig. 4.1 Major steps in an evolutionary cycle of evolvable hardware](image)

4.1.1 Intrinsic/Extrinsic

An Intrinsic hardware evolution and extrinsic case, the phenotype circuits are evaluated in a software simulation during evolution and only the final product is eventually implemented as a real circuit. If all of the detailed characteristics of the implementation could be simulated perfectly, then these two approaches would be equivalent, except for practical
considerations such as speed/cost tradeoffs and the availability of suitable reconfigurable hardware. In this works, the extrinsic approach to the hardware evolution is used for the evolution of digital circuits’ components.

4.2 Evolutionary Design of Digital Circuits

Evolutionary Design of Digital Circuits is designed using complex collections of rules and principles. The design process is top-down in nature and begins with a precise specification. This contrasts very strongly with the mechanisms which have produced the extraordinary diversity and sophistication of living creatures. The designs are evolved by a process of natural selection. Eventually after a number of extraordinarily complex and subtle biochemical reactions an entire living organism is created. The survivability of the organism can be seen as a process of assembling a larger system from a number of component parts and then testing the organism in the environment in which it finds itself. The top-down rule-based space of designs is shown in Figure 4.2 as a small sub-region in the much larger space of all possible designs. A process of human inspiration or accidental discovery, this space is widened as new concepts and principles are developed. Generally restrictive assumptions have to be made about the range of parts which can be used within this space. This is imposed by the constraints of a tractable system of rules. On the other hand, it is argued here that by employing the simple idea of assemble-and-test together with an evolutionary algorithm one can explore the entire design space and use a much larger collection of parts precisely because of the absence of imposed rules of design.
The concept of assemble-and-test together with an evolutionary algorithm to gradually improve the quality of a design has largely been adopted in the nascent field of Evolvable Hardware where the task is to build an electronic circuit. The evolution of digital circuits has been intensively to discern generalisable principles of design and thus, to allow one automatically to produce large and efficient electronic circuits. Digital electronic circuits have been evolved intrinsically and extrinsically. The former is associated with an evolutionary process in which each evolved electronic circuit is built and tested on hardware, while the latter refers to circuit evolution implemented entirely in software using computer simulations. This refers to the very fast growth in the number of gates used in the target circuit as the number of inputs of the evolved logic function is increased. This is an enormous search.
that is difficult to explore even with evolutionary techniques. This increases with the size of the truth table of the evolved circuit.

This task involves the development of the library of components which are used as building blocks for the generation of large scaled circuits. The approach here is:

(i) To identify the digital components which can be used as building blocks for the generation of larger circuits? The identification of suitable building blocks is crucial for the evolution of scaled digital circuits.

(ii) The basic building blocks once identified, then evolve these electronic circuits by using building blocks that are two input gates and two input multiplexers.

(iii) Develop a library of these components. This library serves as the built in library of components for the generation of larger circuits.

4.3 Evolutionary Circuit Design

The idea behind evolutionary circuit synthesis/design is to use a genetic search/optimization algorithm that operates in the space of all possible circuits and determines solution circuits with desired functional response. The genetic search is tightly coupled with a coded representation of the candidate circuits. Each circuit gets associated a “genetic code” or chromosome. The simplest representation of a chromosome is binary strings, (a succession of 0s and 1s) that encode a circuit. Synthesis is the search in the chromosome space for the solution corresponding to a circuit with a desired functional response. The genetic search follows a "generate and test" strategy. A population of candidate solutions is maintained each time; the corresponding circuits are then evaluated and the best candidates are selected and reproduced in a subsequent generation, until a performance goal is reached.

The evolution algorithm begins by initialising the bits of each chromosome with random values. The chromosomes are evaluated in turn by creating a circuit based on the parameter values, either as a simulated model of the circuit or as a concrete circuit embodied in reconfigurable hardware. The circuit’s fitness for performing the target task is measured by
passing it a set of test values and evaluating the veracity of the circuit’s output. The selection operator then probabilistically populates the next generation of chromosomes such that chromosomes with high fitness are more likely to be selected. The operator selects two individuals at random and compares their fitness. Only the individual with the highest fitness is propagated to the next generation. If they have equal fitness the individual to be inserted is chosen at random. Common variation operators are one-point crossover and point mutation. One point crossover recombines two chromosomes by choosing a position at random along the chromosome and swapping every bit beyond this point between the strings. Point mutation independently inverts each bit in the chromosome according to a fixed probability are shown in Figure 4.3.

Fig. 4.3 Process of Evolution
After a number of iterations, the best fit design configuration is obtained. The evolution algorithm is shown in Table 8.

**Table 8 Evolution Algorithm**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Evolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input</td>
<td>P: parameters of the initial edge detector including the threshold</td>
</tr>
<tr>
<td></td>
<td>N: number of configurations</td>
</tr>
<tr>
<td>Output</td>
<td>final configuration bitstream</td>
</tr>
<tr>
<td></td>
<td>(2) generate an initial configuration</td>
</tr>
<tr>
<td></td>
<td>(3) while (not N) and (P is not satisfied)</td>
</tr>
<tr>
<td></td>
<td>(i) Evaluate each configuration Ni</td>
</tr>
<tr>
<td></td>
<td>(ii) Generate a configuration Ni+1</td>
</tr>
<tr>
<td></td>
<td>(iii) Sort configurations</td>
</tr>
<tr>
<td></td>
<td>end while;</td>
</tr>
</tbody>
</table>

### 4.4 Coordinate Logic Operation (CLOs) based Image Enhancement

In CLOs based design, there is often a requirement for a fast partial reconfiguration, including the controllable granularity of configurable elements and a transparent structure of the configuration data. Ideally, a specialized reconfigurable device should be constructed for a given application in order to meet its particular requirements. However, developing an application specific integrated circuit (ASIC) is less feasible for many (mainly economic) reasons. CLBs are, in fact, an implementation of a domain-specific reconfigurable circuit on top of an ordinary programmable hardware device. The designer can construct the CLBs and evolve logic circuits, image filters, sorting networks etc. As the evolutionary algorithm (EA) can be implemented in the same hardware in case of these applications, a fast configuration interface can be established.
On the pessimistic side, the implementation of CLBs is relatively expensive in terms of gates used, since, interconnection circuits are based on area-expensive multiplexers. However, on the optimistic side, they can be designed totally independent of a target platform. Also, they can be utilized (in connection with a hardware implementation of the evolutionary algorithm) to implement soft evolvable IP cores. CLB at the level of IP cores has become an integrated component in a variety of systems. These systems are responsible for completing tasks that are difficult for conventional hardware solutions, for instance, adaptation of functionality, adaptation of sensing, autonomous self-repairing and learning. As a result, there is an increasing interest in the use of CLBs in standalone applications (space applications) and in extreme environments exhibiting increased radiation and temperature levels. The fundamental properties of coordinate logic operations are illustrated in Table 4.2.

<table>
<thead>
<tr>
<th>Table 9 Fundamental Properties of Coordinate Logic Operations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fundamental laws</strong></td>
</tr>
<tr>
<td>0 CAND A = 0, 0 COR A = A</td>
</tr>
<tr>
<td>A = CAND A = A, A COR A = A (idempotence laws)</td>
</tr>
<tr>
<td>(2^n - 1) CAND A = A, (2^n - 1) COR A = (2^n - 1)</td>
</tr>
<tr>
<td>A CAND CNOT(A) = 0, A COR CNOT(A) = (2^n - 1)</td>
</tr>
<tr>
<td><strong>Commutative laws</strong></td>
</tr>
<tr>
<td>A CAND B = B CAND A,</td>
</tr>
<tr>
<td>A COR B = B COR A</td>
</tr>
<tr>
<td><strong>Associative laws</strong></td>
</tr>
<tr>
<td>A CAND (B CAND C) = (A CAND B) CAND C</td>
</tr>
<tr>
<td>A COR (B COR C) = (A COR B) COR C</td>
</tr>
<tr>
<td><strong>Distributive laws</strong></td>
</tr>
<tr>
<td>CAND (A, (COR (B, C))) = COR (CAND (A, B), CAND (A, C))</td>
</tr>
<tr>
<td>CAND (A, (CAND (B, C)))</td>
</tr>
</tbody>
</table>
\begin{align*}
\text{De Morgan’s laws} & \quad \text{CNOT} (A_1 \text{ CAND } A_2 \\
& \quad \text{CAND } \ldots \text{ CAND } A_n) = \\
& \quad \text{CNOT} (A_1) \text{ COR } \text{ CNOT} (A_2) \ldots \text{ COR } \text{ CNOT} (A_n) \\
& \quad \text{CNOT} (A_1 \text{ COR } A_2 \text{ COR} \ldots \text{ CAND } A_n) = \text{CNOT} (A_1 \text{ COR } A_2 \ldots \text{ COR } \ldots \text{ CAND } A_n) \\
\text{Absorption laws} & \quad A \text{ COR } (B \text{ CAND } A) = A, \\
& \quad A \text{ CAND } (B \text{ COR } A) = A \\
& \quad (A \text{ COR } B) \text{ CAND } (A \text{ COR } C) = A \text{ COR } B \text{ CAND } C
\end{align*}

### 4.4.1 Coordinate Logic Dilation (CLD)

CLD of the images \( G \) by the structuring elements \( B \) is denoted by \( G^D_B (g(i,j)) \) or \( G^D_B \).

\[
F = G^D_B = \text{COR } g(i,j) \in E
\]

\[
= \sum_{\substack{k=0 \cr k \leq \delta^D_B g(i,j)}}^{\infty} (s_k(i,j)) B^D, \quad i=1,2,\ldots,M, \quad j=1,2,\ldots,N
\]

\[\ldots(4.1)\]

where \((s_k(i,j)) B^D\) denotes the dilation operations on the binary value \(s_k(i,j)\) by the structuring elements \(B\), given by \((s_k(i,j)) B^D = \text{OR } (S_k (i,j) \in B)\).
4.4.2 Coordinate Logic Erosion (CLE)

CLE of the image \( G \) by the structuring elements \( B \) is denoted by \( G_B^D \) and is given.

\[
F = G_B^E \text{ CAND } g(i,j) = \sum_{k=0}^{n-1} \left( s_k(i,j) \right) \text{ E } B^{2^k}
\]

\( i = 1,2,\ldots,M, \quad j = 1,2,\ldots,N, \quad \ldots \) (4.2)

where \( (s_k(i,j)) \) denotes the erosion operation on the binary values by the structuring elements \( B \), given by \( (s_k(i,j)) = \text{ AND } (s_k(i,j)) \in B. \quad \ldots \) (4.3)

4.4.3 Edge Extraction

Edge extraction in an image \( G \) can be achieved with CL filters using the same approach adopted with morphological filter with the eroded image \( G_B^E \) subtracted from the original image \( G \), so that the edge detector is \( G - G_B^E \). Edges in different orientations can be obtained by using a 1D structuring element. The size of the structuring elements controls the thickness of the edge markers. Among the variety of the CL-based edge detectors, an efficient one that corresponds to the morphological \( G_B^D - G_B^E \) edge detector and given very similar results which is shown in the eqn. [4.4]

\[
[(G_B^E \text{ CXOR } G) - (G_B^E \text{ CXOR } G)]
\]

\( \ldots \) (4.4)

where, \( A \text{ CXOR } B \) represents a measurement of the difference between \( A \) and \( B \).

A novel approach for edge extraction and enhancement is based on the direct application of CL filters to the original image, without using a arithmetic subtraction between images. The edge extraction results is given in eqn. [4.5]

\[
f(i,j) = g(i,j) \text{ CAND } [ \text{ CNOT } [g(i-1,j)] \\
\text{CAND } g(i,j) \text{ CAND } g(i,j)]
\]

\( \ldots \) (4.5)
4.4.4 Evolution Strategies

Evolution strategies approach function optimization problems in the l-dimensional real space by exploiting a real encoding of the objective function parameters. The earliest evolution strategies were based on a population consisting of only one individual. There is only one genetic operator used in the evolution process: a mutation. The evolving phase is illustrated in Figure 4.4. During evolution the center pixel in each kernel is replaced by the VRC output as shown in Figure 4.5. The VRC once evolved is placed in online with the feature extraction (using transforms) and the feature classifier (using clustering/learning networks) as shown in Figure 4.6.

![Fig. 4.4 Evolving phase in Image Enhancement](image-url)
Fig. 4.5 Evolved output

Fig. 4.6 Evolved VRC with the feature extract and classify network
4.5 Reason for choosing EHW for Machined Image Enhancement

The use of EHW for machined image enhancement offers several unique advantages such as:

(i) It doesn’t require any statistical information about the type of noise model used.
(ii) Can be evolved with functional elements. Hence, easily adaptive in nature.
(iii) Can be fabricated as a VLSI Chip on FPGA & hence can be used in on-line.
(iv) Ideally suited for images contaminated by a variety of noise sources and decreasing intensity with state of lighting not known.
(v) Capable of adapting to changing environments automatically (reconfigurable).
(vi) Can evolve computing architectures that are:

a) Less Complicated
b) Highly flexible
c) Cost effective (less cost)

4.6 Image Enhancement using EHW Filter

The implementation of the image enhancement filter is presented. The flexibility and adaptability to remove unmodeled noise types is the purpose of an image filter. Evolvable Hardware (EHW) architecture is proposed to filter the noise present in the machine vision grabbed image. The image filter architecture proposed in this work considers spatial domain approach and uses the overlapping window to filter the signal. The scheme is proposed in such
a way as to preserve more image features with less computation effort. The algorithms presented shall form the basic frame for EHW based implementation of on-line adaptive noise removal systems. The proposed EHW approach provides a better performance when compared to the traditional adaptive filter techniques. Also, the EHW filter provides an improved PSNR and subsequently the features extracted shall exhibit improved correlation with the surface roughness to be estimated. EHW filter gives an improved PSNR and has produced a reconstructed image with enhanced sharpness bringing out the finer details in the machined surfaces. Some reported works on use of magnification schemes for enhancement do exist, but there is degradation and blurring of edges. These effects have been removed the best in the EHW approach.

4.6.1 Image Enhancement Architecture

The EHW is configured to accept nine 8-bit inputs $I_0$ – $I_8$ and produce a single 8-bit output which processes gray-scaled (8 bits/pixel) images. Every pixel value of the filtered image is calculated using a corresponding pixel and its eight neighbors. The operation performed on the selected input pixels depends on the configuration bits downloaded into the configurable memory from fitness evaluation unit. The VRC consists of 25 PEs, four PEs are implemented as a single stage of the pipeline. Each PE can process two 8-bit inputs and produce a single 8-bit output as shown in Figure 4.7.
The image filter architecture proposed in this work considers spatial domain approach and uses the overlapping window to filter the signal and has the flexibility and adaptability to remove even unmodeled noise types.

4.6.2 Evolved Image Operators for Processing

In this research, the function to be performed by each PE (processing elements) or CLBs is selected from a set of evolved operators, such that the evolved circuit is inherently testable without the need for a specialized data path. Another selection criteria is that using the primary inputs and outputs alone, the evolved circuit can be tested. The evolved image processing operators chosen in this work are shown in Table 10.
Table 10 Evolved Image Processing Operators

<table>
<thead>
<tr>
<th>Function Code</th>
<th>Function</th>
<th>Function Code</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>0000</td>
<td>X and Y</td>
<td>1000</td>
<td>X&gt;&gt;2</td>
</tr>
<tr>
<td>0001</td>
<td>X or Y</td>
<td>1001</td>
<td>X&lt;&lt;2</td>
</tr>
<tr>
<td>0010</td>
<td>X xor Y</td>
<td>1010</td>
<td>X&gt;&gt;4</td>
</tr>
<tr>
<td>0011</td>
<td>not X</td>
<td>1011</td>
<td>X&lt;&lt;4</td>
</tr>
<tr>
<td>0100</td>
<td>X+Y</td>
<td>1100</td>
<td>Max(X,Y)</td>
</tr>
<tr>
<td>0101</td>
<td>Abs(X - Y)</td>
<td>1101</td>
<td>Min(X,Y)</td>
</tr>
<tr>
<td>0110</td>
<td>X&gt;&gt;1</td>
<td>1110</td>
<td>X</td>
</tr>
<tr>
<td>0111</td>
<td>X &lt;&lt;1</td>
<td>1111</td>
<td>255</td>
</tr>
</tbody>
</table>

Note: ^ → Ex-OR   >> → Right shift   << → Left shift   & → Logical AND
~ → Complement    → Logical OR
It can be observed from Table 4.3 that the proposed choice of operators is an integration of the general hardware implementation of an image filter with a kernel 3x3. It further employs tree of adders with shifters, equivalent to an implementation of the median filter that employs a network of comparators and multiplexers.

4.7 Algorithm for Image Enhancement using VRC

The algorithm for poor illumination compensation is given as follows:

(i) Input the corrupted and reference images and store it in buffer.
(ii) Generate initial population of size ‘n’ with each other of chromosome length L. Each chromosome contains details about the interconnection between PE’s and also the function performed by the PE.
(iii) For each chromosome in the population.
(iv) Take 3X3 overlapping window and input nine pixel values to the VRC to replace the centre pixel. Every pixel value of the filtered image is calculated using a corresponding pixel and its eight neighbors. This process is repeated for whole image.
(v) Calculate mean difference per pixel (MDPP) and fitness measure.
(vi) Retain the chromosome that has maximum fitness.
(vii) Select parent chromosome according to roulette wheel selection procedure.
(viii) Apply crossover and mutation operations on the selected chromosome to get the next generation strings.
(ix) Replace the old population.
(x) Repeat from steps 3 for ‘N’ number of generations.

4.8 Resource Selection

In Fig. 4.8 there are certain spare resources (CLBs) which coexist along with the active CLBs. Each spare CLB is represented by bit 0 and the active ones are represented by bit 1. For example in Fig. 4.9 the CLBs 3, 5, 10, 12, 18, 20, 23 whose outputs are not given as
inputs to any succeeding columns of CLBs represent spare resources. In this way, the resource utilization in the present work is maximized.

Fig. 4.8 Evolved VRC architecture

In Fig. 4.9 and figure 4.10 the functional and structural decoded architecture output captured online is shown.
Fig. 4.9 Functional decoded logic output
4.9 Scheme for EHW Implementation

If the evolution process is on a local microprocessor or chip then the adaptation does not need to be decided at design time. Thus, the required change in the circuit is easy to evolve dynamically with changing external factors. EHW can be built on software reconfigurable logic devices such as FPGA/PLD. In EHW evolution, the whole system is implemented in the hardware. The FLE (Function Level Evolution) approach is an iterative process and is terminated if the number of noisy pixels remains unchanged or the number of noisy pixels decreases to an accepted level. The block diagram that can be used for EHW implementation of an adaptive noise removal system is given in Figure 4.11. In noise cancellation, the size of the local window and the remote window are typically fixed as 3×3, while the search range window shall be of the size of 7×7. The node array geometry takes the size of 3×8 in the function level evolution. When the difference between output of the filter
and the center pixel of the remote window is less than the predefined value, the circuit is a successfully evolved and function level evolution for the current noisy pixel is terminated.

![Figure 4.11 Block diagram of the basic scheme for EHW implementation](image)

The performances are quantitatively measured by the peak signal-to-noise ratio (PSNR) is given in eqn. [4.6]

\[
PSNR = 10 \log_{10} \left( \frac{1}{MN} \sum_{ij} (o_{ij} - t_{ij})^2 \right)
\]

where, \(o_{ij}, t_{ij}\) shows the pixel values of the restored image and the original image, respectively.

### 4.9.1 Parameters Used

The experimental parameters used in this work are as follows:
(i) Number of rows – 4.
(ii) Number of columns – 6 (usually depend on the size of the circuit to be evolved).
(iii) Level-back = 2 (number of preceding column inputs acceptable).
(iv) Mutation rate - 8% (3 genes).
(v) Number of generations - upto 1000,000.
(vi) Gates used - all the two input gates, and the digital components.

4.10 Evolved VRC

The architecture of a single evolved PE in the VRC is shown in Figure 4.12. Both sel1 and sel2 should not exceed the number of the multiplexer inputs. The sel3 input is the binary representation of the number of functions in Table 4.3. The output of the PE is given by

![Fig. 4.12 Single PE and its configuration](image)

The VRC evolved corresponding to noise removal in the machined image is shown in Figure 4.13. The complete architecture using which the image enhancement (noise removal) is performed is shown in Figure 4.14.
The proposed implementation integrates a hardware realization of genetic algorithm and a reconfigurable device and is shown in Figure 4.14. The ability of the circuit to reconfigure itself under different degradation scenarios is intrinsically present in the architecture.
4.11 Texture of Milled Surface

The results for milled surfaces corresponding to different cutting conditions are discussed. In each case, a noise of mean zero and variance 0.03 is assumed to corrupt the original image. It can be clearly perceived that the proposed EHW filter gives an improved PSNR and has produced a reconstructed image with enhanced sharpness bringing out the finer details in the machined surfaces. The degradation and blurring of edges, which accompanies magnification, has been removed the best in the EHW approach. These results are shown in Figure 4.15.
In this chapter the evolvable hardware based image enhancement filter, its advantages, implementation and filtered results are presented. The proposed EHW filter has used only a local knowledge to enhance the image while a conventional solution will probably need the position of the currently processed pixel. The MDPP is used for evolving the EHW, while PSNR value is used as a measure of the filter performance and for comparative study, conventional image enhancement schemes reported in the literature is used.

Fig. 4.15 Texture of Milled surfaces before and after preprocessing

4.12 Chapter Conclusion

In this chapter the evolvable hardware based image enhancement filter, its advantages, implementation and filtered results are presented. The proposed EHW filter has used only a local knowledge to enhance the image while a conventional solution will probably need the position of the currently processed pixel. The MDPP is used for evolving the EHW, while PSNR value is used as a measure of the filter performance and for comparative study, conventional image enhancement schemes reported in the literature is used.
CHAPTER 5

WAVELET TRANSFORM AND FEATURE EXTRACTION

5.1 Introduction

Development of real-time data-driven pattern classification tools facilitate performance monitoring of complex dynamical systems. To capture the relevant information of the underlying dynamics, real-time analysis of time series for information compression into low-dimensional feature vectors is considered as the critical issue. Time series analysis is a demanding task if the data set is collected at a fast sampling rate, high-dimensional and noise-contaminated. The quality of feature extraction from the observed time-series determines the efficiency of the data-driven pattern classification tools. Feature extraction is based on the local property of an image. To this end, several feature extraction tools, such as Short time Fourier Transform (STFT), Principal Component Analysis (PCA), Independent Component Analysis (ICA), kernel PCA, Dynamic Time Warping, Derivative Time Series Segment Approximation, Artificial Neural Networks (ANN), Hidden Markov Models (HMM) have been developed to accomplish the objective.

5.1.1 Motivation for Wavelets

A measure of the irregularities of the function in term of its high frequencies is yielded by Fourier transform. The disability of this measure to locate the position of the irregularity in the function stems from its non spatial localization. A windowed Fourier transform can be used to get the information about the signal in time as well as frequency domains simultaneously. This transform obtains the irregularities of a function in a spatial region of a fixed size, and the function’s irregularities at various points are measured by translating the window back and forth on the spatial domain of the image. The main drawback of windowed Fourier transforms is that the spatial and frequency resolutions of the transform are fixed. A local feature such as edge cannot be located with a precision higher than the width
of the window function. This limitation is inconvenient since a signal in general has features at arbitrary scales. Lowe has proposed scale-invariant feature transform (SIFT), which provides distinctive, stable, and discriminating features. The main advantage of using such SIFT is the simplicity due to the unsupervised nature. However, the SIFT method is practically classified into semi-supervised since it requires a certain degree of supervision.

In order to avoid this shortcoming, Mallat defined the wavelet transform by decomposing the signal into a family of functions resulting from the translations and dilations of a single function called a wavelet. The wavelet transform can be generalized to any number of dimensions, but for the purpose of image processing, the two-dimensional (2-D) case suffices. Wavelet transforms capture the features of images at all scales. Multi resolution decomposition involves decomposition of an image in frequency channels of constant bandwidth on a logarithmic scale. Wavelets and multi resolution appear in the literature on image processing for a variety of applications, such as singularity detection, image coding using multi scale edges and feature detection. Wavelet packet decomposition (WPD) and Fast Wavelet transform (FWT) have been used for extracting rich problem-specific information from sensor signals.

5.2 Wavelets and its Classification

Time-domain wavelets are simple oscillating amplitude functions of time. Scaling and Translations are the two basic parameters of wavelet representations. The set of all scaled and translated wavelets of the same basic wavelet shape forms a wavelet family. Wavelet based processing offers advantages such as,

(i) They are localized in both time and frequency
(ii) They have large fluctuating amplitudes during a restricted time period and are very low amplitude or zero amplitude outside of that time range.
(iii)Wavelets are band-limited. They are composed of not one but a relatively limited range of several frequencies.
(iv)They provide effective time frequency decomposition of signal over a range of characteristic frequencies that separates individual signal components
(v) The time or space resolution improves as the scale of a signal event decreases.

5.2.1 Reasons for Opting Wavelets

The following characteristics play a major role in usage of wavelets in surface roughness application:

(i) Localizing the occurrence of transients and component event in machined image.

(ii) The wavelet representation is invertible, i.e., original image can be reconstructed from a set of analysis coefficients that capture all of time and frequency information.

Wavelet shape can be selected or designed to match the shape of components embedded in the image. Such wavelets are excellent templates to detect and separate those components and events from the background. The ability to model temporal and spectral properties of specific components of machined images provides optimum resolution of concerned events.

5.2.2 Orthogonal wavelets

In this wavelet, finite support and compact wavelets are more popular due to their relations to multi-resolution filter banks. These wavelets have finite impulse response (FIR) wavelet filters. Among these wavelets, the most commonly used wavelets can be categorized into two classes:

(i) Orthogonal wavelet systems decompose signals into well-behaved orthogonal signal spaces. However, the analysis and synthesis filters are not symmetric, a condition that might be required in some applications like image processing.

(ii) Bi-orthogonal wavelet systems are more complicated and are defined based on a pair of scaling and wavelet functions. Due to more flexibility, the analysis and synthesis
filters can be forced to be symmetric and hence, be useful for applications that demand linear phase filtering.

5.2.3 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) decomposes an input signal into low and high frequency component using a filter bank. Daubechies and Haar wavelets can be used to construct the filter bank, which exhibits properties of orthogonality, linearity, and completeness. For each level, wavelets can be separated into different basis functions for image compression and recognition. The wavelet transform can be used to represent a two-dimensional (2D) signal by the 2D resolution decomposition procedure, where an image is repeatedly decomposed into an approximation and several detail components at each level.

The 2-D extension of Mallat’s algorithm leads to a wavelet transform with three wavelet functions [three wavelet coefficient sub images at each scale, which does not simplify the analysis and the interpretation of the wavelet coefficients becomes an obscure process. Images with fine features in all directions, an isotropic wavelet analysis seems more appropriate. By definition, the wavelet coefficient mean is null.

At a given scale, the transform can provide decimated number of wavelet coefficients. This will not restore the intermediate values without using the approximation at this scale and the wavelet coefficients at smaller scales. Since the multiresolution analysis is based on scaling functions without a cutoff frequency, the application of the Shannon interpolation theorem is not possible. The interpolation of the wavelet coefficients can only be done after reconstruction and shift which has no importance for signal coding.
5.3 Evolved Filters

An evolution in natural systems have inspired the development of a group of powerful yet extraordinarily flexible optimization methods known collectively as evolutionary computation (EC). The modern synthesis derives from work performs, and share the common themes of optimization performed by a competing population of individuals in which a process of selection and reproduction with modification is occurring. EC has the advantage that is flexible, it can derive a fitness measure for a problem, and then the problem might be solved using EC. Many different problems from different domains have been successfully tackled using EC, including: optimization of dynamic routing in telecommunications networks, designing finite-impulse-response digital filters and designing protein sequences with desired structures.

5.3.1 Critical Design Issues

A crucial issue when using EC is how to represent candidate solutions, so that it can be manipulated by EC effectively. To evolve individuals that represent possible image processing algorithms, and so, use a system based upon genetic programming. Genetic programming (GP) is essentially a framework for developing executable programs using EC methods. GP applied to image-processing problems, including: edge detection, face recognition, image segmentation, image compression and feature extraction in remote sensing images.

5.3.2 Use of Genetic Algorithm for feature extraction

Genetic algorithm (GA) is an effective feature selection approach used for finding the optimization weight in order to obtain better image feature extraction results. An optimum weighted Manhattan distance function was designed using a genetic algorithm utilizing the Mantel test as a fitness function. In feature extraction, it’s based on GA whose fitness function combined the number of features to be used and the error rate of the Bayesian classifier was
presented. Hernández proposed using GA to select a set of suitable regions for the feature extraction in facial expression recognition system. Different from these approaches, we represent low-level image features with all the MPEG-7 feature descriptors and use GA taking into account $k$-nearest neighbor ($k$-NN) classification accuracy as fitness function for feature selection. Four parameters are considered to do the task: weight optimization, the selection of optimum feature descriptor subset, weight optimization followed by the selection of optimum feature descriptor subset and the selection of optimum feature descriptor subset followed by subset weight optimization. When optimizing weights, a real coded chromosome GA and $k$-NN classification accuracy as fitness function are used. In the selection of feature descriptor subset, a binary one is used and fitness function takes into consideration $k$-NN classification accuracy combining with the size of feature descriptor subset.

5.4. Genetic operation

GA searches for better solutions by genetic operations, including selection operation, crossover operation, mutation operation and etc. Selection operation is to select elitist individuals as parents in current population, which can generate offspring. Fitness values are used as criteria to judge whether individuals are elitist. A reference preserved model for selection operation is employed. In order to acquire the fittest individual in the history when GA process ends, after crossover and mutation operations in each GA iteration, both parent and up-to-date solutions are put into a pool to select $N$ individuals with the top highest fitness values to form the new population. Crossover operation needs to be operated on two individuals with crossover rate $P_c$. Firstly, all of the parent individuals are combined and pairs are obtained. Secondly, randomly generate two numbers and $b$ with predefined length for each chromosome. Mutation operation is very important in keeping the varieties of populations. The individuals generated in crossover operation into the pool with parent individuals. The worst fit individuals are selected with a very small mutation rate. This method adjusts the GA process, which lets mutation operation has larger mutation ranges in earlier stage, and smaller ones in the later.
5.4.1 Termination criteria

We proceed with the next generation until the process reaches the maximum iteration $Genmax$. When the process ends, the fittest individual is output as the optimum feature selection result. The choice of GA is used to evolve the best filter configuration that is used to perform image enhancement.

5.5 Implementation Schemes

In this work, the basic recursive pyramidal DWT filter scheme is used for feature extraction from the machined image. A ‘best basis’ decomposition is defined as the pathway through the filtering tree that captures the information in a most efficiently. Wavelet transforms offer flexible options to choose basis functions for analyzing time-varying waveforms. The output of the low pass filter is the set of DWT coefficients associated with a set of companion functions called ‘scaling functions’. The high pass coefficients used to create a component waveform known as ‘detail functions’. The core wavelet of a DWT is referred as ‘mother wavelet’. DWT uses wavelets as octave harmonic filters, holding the ratio of the center frequency of the wavelet filter to its bandwidth constant across scales. There are two methods for selecting basis functions namely

1. Matching pursuit technique
2. Direct design technique provided by matched wavelets.

In this work, the ability of the wavelets, such as increased power to resolve transient and scale-specific events in image datasets, to efficiently store and transmit images and to observe and quantify their small-scale structure in time and space, is fully explored. In the wavelet Transform operation, all the subbands of the lower resolution image must be refined (i.e., a rate added), which is given in eqn. [5.5],

$$\sigma_{wgm}^2 = \prod_{m=1}^{M} \left( \sigma^2_m \right)^{N_m/N} \quad \ldots (5.1)$$
Let (1) $M=7$ [the number of subbands] and 
(3) the number of dyadic decomposition stage is two as shown in Figure

![Fig. 5.1 Decomposition stage](image)

From Fig. 5.1

From Fig. 5.1

\[
\frac{N_1}{N} = \cdots \quad \frac{N_4}{N} = \frac{1}{16} \quad \text{and} \quad \frac{N_5}{N} = \cdots \quad \frac{N_7}{N} = 4
\]

Thus, in eqn. (5.1),

\[
\sigma_{\text{wgm}}^2 = [\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2]^{1/16} \cdot [\sigma_5^2, \sigma_6^2, \sigma_7^2]^{1/4}
\]

\[
= [\sigma_{\text{wgm(base)}}^2]^{1/4} \cdot [\sigma_{\text{wgm(enh)}}^2]^{3/4}
\]

\[
\quad \cdots (5.3)
\]

where,

\[
\sigma_{\text{wgm(base)}}^2 = (\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2)^{1/4} \quad \text{and} \quad \sigma_{\text{wgm(enh)}}^2 = (\sigma_5^2, \sigma_6^2, \sigma_7^2)^{1/3}
\]

Thus, the resolution rate is low for subbands 1 to 4 and high for all subbands, represented as $R_{i}^{(1)}$ and $R_{i}^{(2)}$ respectively.

\[
\therefore R_{i}^{(1)} = R + \frac{1}{2} \log_2 (\sigma_{\text{wgm(base)}}^2) \quad \text{i} = 1,2,3,4 \quad \cdots (5.4)
\]

\[
R_{i}^{(2)} = R + \frac{1}{2} \log_2 (\sigma_{\text{wgm}}^2) \quad \text{i} = 1 \text{ to } 7 \quad \cdots (5.5)
\]

After simplification,

\[
R_{i}^{(2)} = R_{i}^{(1)} + \frac{1}{2} \log_2 \left( \frac{\sigma_{\text{wgm(base)}}^2}{[\sigma_{\text{wgm(base)}}^2]^{1/4} \cdot [\sigma_{\text{wgm(enh)}}^2]^{3/4}} \right) \quad \cdots (5.6)
\]

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eqn. [5.6] specifies the relation that $\sigma_{wgm}^2 \text{(enh)}$ shall be less than $\sigma_{wgm}^2 \text{(base)}$, so that, $R_i^{(2)} > R_i^{(1)}$ for $i = 1$ to 4. This necessitates that all the subbands of the lower resolution image must be refined i.e., have a rate added to them and this is carried out in this research.

5.6. Algorithm for Wavelet Based Feature Extraction

Feature extraction is the first step in a feature tracking algorithm, hence, it is important that the features have well-defined edges with the contour information well preserved. The scheme proposed to extract features is detailed below as shown in Figure 5.2.

Step 1: Apply discrete wavelet transforms to the input image, and generates a wavelet plane.

Step 2: Make all insignificant wavelet coefficients, i.e., all coefficients below a user-specified (often depends on the application) value, zero.

Step 3: Reconstruct the image with the remaining coefficients.

Step 4: Choose a threshold, and select the edges.

Step 5: If the edges are not satisfactory, decrement the threshold and go to Step 4).

![Fig. 5.2 Flowchart for Wavelet Transform Based Feature Extraction Algorithm](image-url)
Such a scheme has several advantages over the discrete wavelet transform, which are,

(i) Transform can be carried out using integer values leading to exact reconstructions at various scales as there will not be any errors due to round off.

(ii) Structure contours are preserved while the noise is suppressed.

(iii) The algorithm can be easily modified to work on intermediate scales.

In this research the different feature extraction modules using DWT are developed such that the code acts as a communication interface between user and database. This database is repertoire of machined images enhanced with an evolved filter. These are discussed is shown in Table 11.

**Table 11 Detail of Machined images enhanced with an evolved filter**

<table>
<thead>
<tr>
<th>Type of Segment</th>
<th>Description</th>
</tr>
</thead>
</table>
| (i) Interactive image reading segment | • The code interacts with the user by providing ‘browse’ option and offers a dialog box that lists grabbed enhanced images in the folder, and  
• Enables the user to select an image with the specific extension, which will be subjected to various operations for extracting feature. |
| (ii) Wavelet Selection, Decomposition Vector Calculation and Energy calculation | • An operational platform in discrete wavelet domain possessing symmetric padding extension fixes by segment.  
• The user selects a wavelet function from a given set of functions.  
• By using the decomposition vector as input, energy levels corresponding to |
approximation and details coefficients are computed.

(iii) Coefficient Extraction from decomposition vector and display

- A segment is fed with decomposition vector as input, which uses different functions, namely
  - (i) approximation_coeff_calc,
  - (ii) detail_coeff_hor_calc,
  - (iii) detail_coeff_ver_calc,
  - (iv) detail_coeff_dia_calc for decomposition.

  These functions perform extraction operation on decomposition vector and yields approximation coefficients, horizontal coefficients, vertical coefficients and diagonal coefficients.

(iv) Coefficient Reconstruction from decomposition structure

- Segment performs two functions, reconstruction of coefficients from decomposition structure and scaling.
- A function, reconstruct_coeff is used to reconstruct coefficients by accepting decomposition structure, decomposition level and produces approximation coefficients, horizontal coefficients, vertical coefficients and diagonal coefficients.
5.7 Feature Extraction Results

The result obtained by applying the wavelet based feature extraction algorithm is an original enhanced milled image.

![Fig. 5.3 Original enhanced milled image](image1)

![Fig. 5.4 Wavelet decomposition tree (left figure) and data for node (4,3) (right figure)](image2)

The energy details obtained for the milled image is shown in Table 12. The last column \( E_{\text{di}} \) in Table 12 is the average of \( E_{\text{Hi}}, E_{\text{Vi}} \) and \( E_{\text{di}} \) for level ‘i’. These average energy
values can be used as input to a feature classifier network for predicting the surface roughness in future.

Table 12 Evaluation of the different values

<table>
<thead>
<tr>
<th>i-values</th>
<th>Eai</th>
<th>Ehi</th>
<th>Evi</th>
<th>Edi</th>
<th>Eti</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>99.9507</td>
<td>0.0415</td>
<td>0.0047</td>
<td>0.0031</td>
<td>0.016433333</td>
</tr>
<tr>
<td>2</td>
<td>99.6876</td>
<td>0.013985</td>
<td>0.0116</td>
<td>0.00475</td>
<td>0.010111667</td>
</tr>
<tr>
<td>3</td>
<td>99.1891</td>
<td>0.242633</td>
<td>0.017</td>
<td>0.010633</td>
<td>0.090088667</td>
</tr>
<tr>
<td>4</td>
<td>99.2522</td>
<td>0.168425</td>
<td>0.011825</td>
<td>0.00875</td>
<td>0.063</td>
</tr>
</tbody>
</table>
CHAPTER 6

RESULTS AND DISCUSSION

6.1 Results of image enhancement filter

Images usually acquired through modern cameras may be contaminated by a variety of noise sources and decreasing intensity and in most cases the type of noise and state of lighting are also not known apriori. There is a need for design of recognition systems with filtering capability to adapt to changing environments automatically. This requires computing architectures that are less complicated, highly flexible and more cost-effective as compared to the traditional ones, which calculates the coefficients of a general-purpose model. The results obtained by using the EHW based image enhancement filter are presented in this section. The PSNR improvement obtained by using the EHW based image enhancement for both milling and grinding process. The histogram of original image and filtered image is shown in figure 6.1 for two sample cases. All the approaches used to enhance image quality using computer vision, application of EHW techniques to the grabbed image was found to be the most effective method. Hence, this technique can be efficiently used for non-contact inspection of components, which has assumed considerable significance.

The estimation of $G_a$ (optical roughness value) after applying EHW technique had a better correlation (i.e. higher correlation coefficient) with the average surface roughness ($R_t$) measured using a conventional and widely accepted stylus type instrument for the components manufactured particularly using milling and grinding processes. Also, the PSNR value is found to be best in the EHW based scheme. The higher PSNR indicates a better resolution and degradation and blurring of edges gets removed to a large extent. It is worth mentioning that this improvement is significant for the milled surfaces compared to the ground surfaces. This trend can be explained from the fact that there is a large local variation in the characteristic of ground surface, as compared to the more uniform and fine milled surfaces resulting in better correlation between stylus $R_t$ and vision roughness $R_t$ for milled surfaces.
6.2 Results of feature extraction network

The sequence of operations involved in the estimation of $R_t$ in this approach is shown in figure 6.2. The energy details for 12 sample cases for milling and grinding process is shown in table 13 and table 14 respectively. The average of these energy values are obtained and given as input to the feature classifier network. The results are presented separately for milled and ground surfaces in the following sections.

Figure 6.2 Surface roughness estimation of raw image with WT features
Table 13 Experimental Milling parameters (WT) and surface roughness for verification tests

<table>
<thead>
<tr>
<th>Test No.</th>
<th>Machining Conditions</th>
<th>Features of image texture</th>
<th>Stylus Vision</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>V (m/s)</td>
<td>F (m/rev)</td>
<td>D (mm)</td>
<td>E_h</td>
</tr>
<tr>
<td>M1</td>
<td>250</td>
<td>40</td>
<td>1.6</td>
<td>0.1166</td>
</tr>
<tr>
<td>M2</td>
<td>500</td>
<td>40</td>
<td>1.6</td>
<td>0.3037</td>
</tr>
<tr>
<td>M3</td>
<td>500</td>
<td>80</td>
<td>1.6</td>
<td>0.3177</td>
</tr>
<tr>
<td>M4</td>
<td>1000</td>
<td>40</td>
<td>0.4</td>
<td>0.2081</td>
</tr>
<tr>
<td>M5</td>
<td>1000</td>
<td>80</td>
<td>0.8</td>
<td>0.2210</td>
</tr>
<tr>
<td>M6</td>
<td>1000</td>
<td>160</td>
<td>0.4</td>
<td>0.2293</td>
</tr>
</tbody>
</table>

Table 14 Experimental grinding parameters (WT) and surface roughness for verification tests

<table>
<thead>
<tr>
<th>Test no.</th>
<th>Machining conditions</th>
<th>features of image texture</th>
<th>Stylus Vision</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>V (m/s)</td>
<td>F (m/rev)</td>
<td>D (mm)</td>
</tr>
<tr>
<td>G1</td>
<td>23.55</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>G2</td>
<td>23.55</td>
<td>10</td>
<td>25</td>
</tr>
<tr>
<td>G3</td>
<td>23.55</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>G4</td>
<td>26.17</td>
<td>10</td>
<td>25</td>
</tr>
<tr>
<td>G5</td>
<td>26.17</td>
<td>15</td>
<td>25</td>
</tr>
<tr>
<td>G6</td>
<td>32.71</td>
<td>10</td>
<td>5</td>
</tr>
</tbody>
</table>
6.2.1 Energy map details for milling

The complete energy map details for milled sample case is shown in figure 6.3. The original enhanced machined image for sample case is also shown in figure 6.4.

Figure 6.3 Complete energy map details for the milled image (four level decomposition)
6.2.2 Energy map details for grinding

The complete energy map detail for sample case is shown in figure 6.5. The original enhanced machined image for the sample case is also shown in figure 6.6.
6.2.3 Variation of energy values with $R_t$

The variation of energy values with $R_t$ for 12 sample cases is shown in figure 6.7 and 6.8 for milling and grinding images respectively. These variations clearly show that there is a significant correlation present between the surface roughness $R_t$ and the decomposed energy values of the machined image.
6.3 Results of feature classification network

The performance of the ANN based feature classification and the estimation of surface roughness is presented in this section. The estimated $R_t$ is compared with the standard stylus values and it is observed that there is less deviation between the vision $R_t$ and the stylus $R_t$. The results are presented separately for milling and grinding process in figure 6.9. The estimation error for the 12 verification samples is shown in figure 6.10 (for milling) and figure 6.11 (for grinding).
Figure 6.9 Comparison between predicted roughness values using vision approach and stylus approach for Milling and Grinding process

Figure 6.10 Surface roughness estimation error for milling and grinding Surfaces
Figure 6.11a Variation of milling parameter speed with sample

Figure 6.11b Variation of milling parameter DOC with sample

Figure 6.11c Variation of milling parameter Feed with sample
Figure 6.11d Variation of milling parameter PSNR with sample for 3 approaches

Figure 6.11e Variation of milling parameter $R_t$ with sample

Figure 6.12a Variation of grinding parameter speed with sample
Figure 6.12b Variation of grinding parameter DOC with sample

Figure 6.12c Variation of grinding parameter Feed with sample
Figure 6.12d Variation of grinding parameter PSNR with sample for three approaches

Figure 6.12e Variation of grinding parameter $R_t$ with sample
Milled Surfaces Vs Ground Surfaces
Figure 6.13a Comparison of speed with sample for milled and ground Surfaces

Figure 6.13b Comparison of DOC with sample for milled and ground Surfaces
Figure 6.13c Comparison of Feed with sample for milled and ground Surfaces

Figure 6.13d Comparison of Vandewalle approach with sample for milled and ground Surfaces
Figure 6.13e Comparison of Keren approach approach with sample for milled and ground Surfaces

Figure 6.13f Comparison of Propagation Algorithm approach with sample for milled and ground Surfaces
6.4 Conclusion

The advantages of the present approach are the non-contact measurements and ease of automation. This work has described the use of machine vision techniques to inspect the surface roughness of a work piece under various milling and grinding operations. The machined surfaces using milling and grinding for mild steel with a surface finish range of $R_t$ 1.57 $\mu$m to 85.16 $\mu$m for grinding and 2.5$\mu$m to 143.7 $\mu$m for milling are evaluated in this work using a machine vision system. The results obtained in the present work clearly indicate that the machine vision approach can be effectively used to evaluate the surface finish of machined components. The image enhancement algorithm presented in this work is unique, and is ideally suited for a real time environment, where no apriori information is available about the noise mixed with the captured image. In comparison to conventional non-adaptive filters (which perform well only as long as the spatial density of the impulse noise is less), the EHW based filter presented in this work can handle impulse noise even with higher probabilities and also can preserve sharpness and detail while smoothing non-impulse noise. Conventional filtering schemes may employ various image filters for different scenarios but it is very difficult and time consuming to find a set of appropriate filters and as a result most of
them are suited for off-line implementation only. On the contrary, the proposed structure has the advantage that it does not require any expert knowledge to find the type and order of filters for a given domain.

The image features using wavelet Transformation (E_t, E_h, E_v and E_d) are calculated for the enhanced milling and ground surfaces. An ANN is used for predicting the roughness values of the same components using the above roughness parameters as input. The predicted surface finish values using ANN are found to correlate well with the conventional stylus surface finish (R_t) values.

Several verification tests have shown that the maximum absolute error between the surface roughness measured by vision system and that measured by the stylus instrument is less than 10% for milling and limited to 16% for grinding. Thus, the developed machine vision based surface roughness evaluation can be effectively used to measure the surface roughness over a wide range of cutting conditions in milling and grinding. Therefore, this concept could be used for milled and ground surfaces and easily be extended for estimation of roughness of surfaces manufactured by other processes such as shaping and broaching.