CHAPTER 2

LITERATURE SURVEY

Surface characterisation is vital for design, manufacture and inspection. With the advent of automation, surface characterization needs to be totally computerized so that the task of inspection of surfaces is greatly simplified. In this regard, there has been larger interest in the development of methods for the inspection of surfaces.

Recent research works have shown that computer vision has real potential when applied to the automated measurement of engineering component silhouettes, internal contours, surfaces and profiles. Inspection for surface finish is one such area where investigators are trying to automate. Many investigations have been performed to inspect surface roughness of work piece based on computer vision technology. The practical surface roughness instruments based on computer vision technology are yet to find its acceptance in industries, the reason being the number of options available for capturing the images, processing the images and inference of the data. The research work is driven in these areas and has been always tried to improve the evaluation accuracy. This review is based on these aspects and the different research works done are discussed.

The three main functions of any image processing system are image acquisition, image analysis and image interpretation. In the studies on roughness measurement using machine vision, these functions are carried out by different means, each having its own characteristics. Figure 2.1 shows the
overall variables in this study on surface roughness evaluation using machine vision. The review of the work done related to each function is discussed.

![Diagram of Machine Vision Process]

**Figure 2.1 Variables in the characterisation of surfaces by machine vision**

### 2.1 IMAGE ACQUISITION

Image acquisition is the process of acquiring the surface image data and storing it in appropriate form for further analysis. The evaluation of the surface by machine vision entirely depends on the image. Hence, capturing of image at the right conditions is always important. Image acquisition is normally accomplished by using a camera and stored in the digital form by a digitising system. The type of camera, the lighting arrangement, the resolution of image and the magnifying lens affect the quality of image and hence, further processing.

The surface image can be captured by using a Vidicon camera or a CCD camera. Though Vidicon cameras are commonly used for on-line
inspection, solid-state cameras are widely used for machine vision application for its compactness and digital provisions.

Luk et al (1989) used a CCD camera with microscopic optical system in their study on surface roughness by machine vision system. A 12-W collimated white light source was used to illuminate the inspected surface. The images were digitised for 512 x 512 x 8 resolution. The experimental setup consisted of a lighting fixture with the adjustment for source to object distance and the angle of illumination.

Zhang and Gopalakrishnan (1996) studied fractal geometry of the image captured using a CCD camera with fiber optic lighting. The lighting arrangements had provisions for adjustment of different angle of incidence and different orientation with respect to machined surface. The source light intensity was adjusted at different levels by adjusting the current settings.

On characterization study of machined surfaces Gupta and Raman (2001) used a CCD camera and a 5 mW laser light source for illuminating the surface. Gadelmawla (2004) studied characterisation of surface using grey level co-occurrence matrix and used the microscopic optics and CCD camera for capturing the surface of the specimen. The images were digitised for 760 x 570 x 16 pixels resolution.

Damodarasamy and Raman (1991) studied texture analysis of surfaces using machine vision. A CCD camera with incandescent lighting and Light Emitting Diode (LED) were used for capturing the surface. Priya and Ramamoorthy (2007), in their study on surface evaluation of inclined surfaces, captured the specimen using a CCD camera with the image resolution of 768 x 565 pixels. The illumination was accomplished using a
diffused light source and the angle of incidence was kept approximately $45^\circ$ to the specimen surface.

From the reported literature works, it can be inferred that the surface image can be captured by many methods, and different lighting can be used for illumination. It is observed that the CCD cameras are widely used in surface roughness studies. The CCD cameras are used with microscopic optical arrangement for capturing the magnified surface image of the specimen. In some of the application a magnifying lens is attached to the camera and images are captured directly. In the studies it is observed for medium rough surfaces, conventional lighting arrangements are used at an approximately $45^\circ$ to the specimen surface.

### 2.2 IMAGE ANALYSIS

Image analysis is the manipulation of images using computer algorithms to enhance, restore and understand the information contained in them. Many different methods of manipulation are used in image processing. In surface evaluation using machine vision, a few of the image processing techniques have been used. Generally, the analysis of surfaces can be grouped as spectral, structural and statistical techniques. Spectral techniques are preferred when the texture shows strong periodicity. Structural techniques use pattern primitives for analysis. Statistical approaches are based on the statistical features of the pixel distribution. The image analysis for surface evaluation is also driven by these concepts. The statistical approaches and the spectral approaches are finding wide applications in image analysis. Structural techniques are less used, as it is difficult to develop pattern primitives of different roughness.
2.2.1 Intensity Histogram Method

The scattered light image of the illuminated surface captured by the vision system is considered to be uniquely characteristic of the given machined surface (Griffiths et al 1994). The intensity pattern of the pixels in the image varies with the surface roughness. A plot of intensity distribution of the pixels of such images shows distinction in the histogram curve (Gadelmawla 2001). The statistical parameter associated with such histogram form a basis for the quantification of surface roughness. Figure 2.2 shows one such histogram constructed by Hoy and Yu (1991) for turned surfaces having different roughness.

![Optical intensity histogram for turned surfaces (Hoy and Yu 1991)](image)

Luk et al (1989) constructed grey level histograms for the grey scale images of pattern of scattered light from samples of ground surfaces. The range and the mean value of the distribution were found to increase with the roughness. A unique relationship between the defined optical parameter
R1 (SD/RMS) and average roughness $R_a$ by stylus instrument for different materials like steel, copper and brass was established.

Specimens were machined by turning for wide range of roughness, and the images studied by Hoy and Yu (1991). The optical intensity histogram constructed for the different specimens showed that varying rough surfaces have their own characteristics.

Damodarasamy and Raman (1991) studied the intensity of light along a straight line parallel to the machining marks with LED light source. A qualitative evaluation of the surface was made and was concluded that the spread and the height of intensity curve varied with surface roughness.

Twelve different vision-based optical parameters retrieved from the images were investigated by Gupta and Raman (2001). The parameters were based on the features of the histogram, such as the maximum intensity, height of the curve, width of the curve, second moment of the intensity distribution, etc. On analysis, it was found that the two parameters R1 and $S_{MOD}$ were significant and clearly distinguished different surface gratings.

Sodhi and Tiliouine (1996) used the speckle image statistics for quantification of roughness. The area of bright spot at the center of the reflecting surface varied with the roughness. The area was used as a measure for quantifying roughness. The application of the optical roughness parameter R1(SD/RMS) for online monitoring of surface grinding operation was also demonstrated.

In their work by direct imaging method, Kiran et al (1996) constructed histogram for surfaces machined by shaping, milling and grinding
operation. The possibility of characterising different machined surfaces and the discrimination visible in the intensity histogram was demonstrated.

2.2.2 Fast Fourier Transform Method (FFT)

This method analyses the surface based on the periodicity of texture pattern of the pixels. The FFT approach characterises the image in terms of discrete frequency components. The magnitude of frequency component indicates the degree of presence of the periodically occurring feature. It is useful in indicating the roughness components due to primary lay marks, tool wear marks and vibrations. The magnitude of each frequency component in the image is displayed as a part of proportional intensity in the FFT at an x-y location in the frequency plane. Region of spots in the FFT which appear very bright indicates the presence of a significant frequency component with a given x-y orientation in the original image (Gonzalez 2002). Hence, FFT represents the image signature of the given surface image, which contains irregularities of different spacing in all directions of traverse. A surface image of a casting component having $R_{\text{max}}$ of 12.5 $\mu$m and the corresponding power spectrum after applying the Fourier transform on the image as obtained by Tsai et al (1999) in classification of castings is shown in Figure 2.3.

Hoy and Yu (1991) applied the 2D Fourier frequency transforms on both milled and turned surfaces. The primary lay mark spacing of the rough and smooth surfaces with that of the bright spots in the FFT of the image was correlated. A visual comparison of the FFT of rough specimens and standard specimens was made and the possibility of automated analysis of the image was explored.
Figure 2.3  Surface image of a casting specimen and its power spectra in 3-D perspective (Tsai et al 1999)

Roughness features of cast surfaces in the spatial frequency were extracted using the 2-D Fourier transform (Tsai and Tseng 1999). The castings have random irregularities and hence, the spread of the frequency components in the power spectrum is isotropic and the shape approximates a circle. The magnitude of the power spectrum for frequency components is reduced rapidly for rougher surface. The radius of the spread and the energy in the region in different regions of the frequency domain was extracted as roughness features. It was inferred that the average energy at the four ring regions are approximately monotonic with the surface roughness $R_{\text{max}}$.

Lee et al (2004) in their measurement of surface roughness of turned parts, used two FFT parameters, the major peak frequency and the principal component squared along with the statistical parameter standard deviation. It was shown that the surface roughness of turned specimen
machined with wide range of turning condition could be measured with a reasonable accuracy with the machine vision system.

Five roughness features namely, major peak frequency, principal component squared, average power spectrum, central power spectrum and the ratio of major axis to minor axis based on the Fast Fourier Transform of the images were studied by Priya and Ramamoorthy (2007). The images were captured with the specimen at different inclination. A shadow removal algorithm was applied on the image and the optical roughness features were estimated. The stylus roughness of the specimen $R_a$ was predicted with reasonable accuracy with the optical roughness features.

2.2.3 Grey level Co-occurrence Matrix (GLCM)

The Grey Level Co-occurrence Matrix (GLCM) is a 2-D matrix with the same size as the number of grey levels in the image. It is constructed by specifying a displacement vector $d(dx, dy)$ and then counting the number of pixel pairs (base pixel and neighbour pixel) which have grey level $(i, j)$ and separated by vector ‘$d$’. If the position vector is specified as $(1, 1)$, then the base pixel is compared with one pixel to the right and one pixel below. All such occurrences are counted and entered in the $(i, j)$ location in the GLCM matrix. The GLCM matrix can identify the periodicity of the features and the distribution of the grey level intensity. Figure 2.4 shows the method of calculating the GLCM for a simple image of size $7 \times 7$. It is assumed to have a grey scale of 0-5. The matrix is constructed for symmetrical as well as non-symmetrical positions.
Haralick et al (1973) have described 28 computable texture features based on the grey tone dependencies. The features were used in the application of category identification tasks for three different kinds of images.

For the image analysis ground, shaped and milled surfaces, machined with different cutting parameters were studied by Venkatramanappa and Ramamoorthy (1996) The average run length parameter and run length matrix were estimated from the co-occurrence matrix, for classifying the textures.

Gadelmawla (2004), in his study on surface evaluation selected lapped specimen and machined samples for analysis. The 2-D and 3-D plots of the GLCM were applied to distinguish surfaces of different surfaces. Four parameters namely, the maximum occurrence of the matrix (MOM), maximum occurrence position (MOP), maximum width of the matrix (MWM) and standard deviation of the matrix (SDM) were calculated from the co-occurrence of the matrix. The parameters were found to be useful as roughness indicators and concluded that the maximum width of the matrix (MWM) was the best suitable parameter for correlating with the stylus roughness.
2.2.4 Arithmetic Average of Grey Level (AAGL)

Arithmetic average of the grey level is based on the distribution of grey level along a line feature. It is the average of deviations of the selected grey level distribution from the mean grey value. It is expressed as

\[ G_a = \frac{1}{n} \sum_{i=1}^{n} |g_i - g_m| \]  

(2.1)

where \( n \) is the number of pixels in the distribution
\( g_1, g_2, \ldots, g_n \) are the grey values of a surface image along the line
\( g_m \) is the mean of the grey values and this can be determined by

\[ g_m = \frac{1}{n} \sum_{i=1}^{n} g_i \]  

(2.2)

Lee and Tarng (2001) captured the surface image of turned components machined with different cutting conditions. The arithmetic average of the grey level along with the cutting conditions were correlated with roughness measured with stylus instrument by using a polynomial network. The prediction of roughness using arithmetic average of grey level was made with reasonable accuracy.

Kumar et al (2005) in their studies on surface evaluation have magnified the surface images using digital techniques. A good linear relationship between arithmetic average of grey level estimated from the magnified images and R_a was established at higher level of accuracy.
Ho et al (2002) and Lee et al (2005) used this parameter in their study and found that $G_a$ can give good prediction of $R_a$ along with the cutting conditions.

From the studies it can be inferred that many image based optical roughness features can be retrieved from the image. Some of the parameters are based on the intensity frequency distribution of the pixels in the image. Some of them are based on the frequency distribution in the spatial domain. However in the study it can be observed that no particular parameter is reported as unique in distinguishing roughness.

2.3 INTERPRETATION OF IMAGES

Investigators have retrieved different image based roughness parameters from the image. For interpreting and correlating with stylus roughness, mathematical and non-mathematical tools have been used. The review of some of the works done in this field is presented below.

2.3.1 Statistical Methods

Statistical methods were widely used for interpreting the details of the image. Gupta and Raman (2001) used a random effect three-factor factorial model with cutting speed, lighting condition and spindle speed as factors affecting the image parameter in the study. A linear statistical model was developed along with the analysis of variance. The results showed that the roughness was mostly affected by the cutting speed, whereas the other factors did not have any effect on the roughness.
Tsai and Tseng (1999), in the classification of cast surfaces, described a set of roughness features from the power spectrum of the image. The roughness features were based on the average energy available at the four rings of the power spectrum of the image. A statistical classifier based on the Bayes’ theorem was used for classifying the observed surface to one of the possible roughness class. The statistical classifier assumes that the feature vector is a multivariate Gaussian distribution. For most of the images, the classifier distinguished surfaces of different roughness. But, with second stage Bayes classifier which is derived from the binary image, the roughness were classified with 100% accuracy.

A multiple linear regression equation to predict the surface roughness for surfaces produced with different process was developed by Kumar et al (2005). The machining parameters such as speed, feed, depth of cut and the optical parameter $G_a$ were used for evaluating the surface roughness.

Younis (1998) investigated the image-based parameter Grey level coefficient that indicates the relationship between the grey level at any point to the surrounding point. A unique relationship between the optical roughness parameter and the stylus roughness was obtained from the experiments. The coefficient of variation of the optical method was reported as 8.6% compared to 15% for the Talysurf method.

2.3.2 Artificial Neural Network (ANN)

The advantage of an Artificial Neural Network is that it provides a model-free approach without knowing the exact discriminator function between the input features and the output targets. An ANN is specified by the
topology of the network, the characteristics of the nodes and the processing algorithm.

A four-layer back propagation neural network with varying input feature vectors was used by Tsai and Tseng (1998). The different combination of the roughness features, derived from the average energy of the power spectrum of the image, was investigated for zero classification error of the output parameter $R_{\text{max}}$. Based on the classification of effectiveness and computational efficiency, few of the roughness features were selected as the best-input vector to the neural network.

Priya and Ramamoorthy (2007) used roughness features extracted from the 2-D Fourier transform of the image. The roughness feature extracted from the image was used as input for the analysis. By using a 4-layered neural network, they were able to predict closely the stylus surface roughness with a correlation coefficient of 87%.

2.3.3 Polynomial Network

Polynomial network can be recognized as a special class of biologically-inspired networks with machine intelligence and can be used effectively as a predictor for estimating the outputs of complex systems (Montgomery and Drake 1991, Ivakhnenko 1971, Lee et al 1999). The polynomial network has self-organized adaptive learning ability. In polynomial networks, complex systems are decomposed into smaller simple subsystems and grouped into several layers using polynomial functional nodes. Input of the network are subdivided into groups and then transmitted to individual functional nodes. These nodes evaluate the limited number of inputs by a polynomial function and generate an output to serve as an input to
subsequent nodes of the next layer. This methodology of dealing with a limited number of input at a time, then summarizing the input information and then passing the summary of information to a higher reasoning level is related to human behavior.

Lee and Tarng (2001) used the polynomial networks for predicting surface roughness based on the cutting parameters for surface preparations and optical roughness feature from the captured images. The cutting conditions in turning like cutting speed, feed, depth of cut and the image parameter $G_a$ were given as input to the network. The best network structure was determined using a special algorithm. The predicted $R_a$ by the polynomial network was consistent and the maximum error was $\pm 14\%$.

The features extracted form the Fourier transform along with the cutting conditions were used by Lee (2004) and prediction of the roughness was made by the polynomial network with a maximum error of $\pm 14.96\%$.

2.3.4 Artificial Neuro-Fuzzy Inference System (ANFIS)

Artificial Neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive fuzzy neural network. By using a hybrid learning procedure, it can construct an input-output mapping based on human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. It is found efficient in non-linear mapping. Ho et al (2002) used Artificial Neuro-Fuzzy Inference System (ANFIS) to model the relationship between the features of the surface image and the stylus surface roughness. Once the cutting conditions and grey level of the surface image are given as input to the ANFIS system, the stylus surface roughness can be accurately predicted. Compared to Polynomial Network method ANFIS had
Lee et al. (2004) used the image-based parameter alone, like spatial frequency, arithmetic mean and standard deviation of grey level in the developed ANFIS and showed that the maximum absolute deviation was ±8.71%.

The literature review indicates that many tools can be used for correlating the optical parameters with the stylus roughness. Researchers have used Regression analysis, Artificial Neural Network (ANN), Polynomial Network (PN), Artificial Neuro-Fuzzy Inference System (ANFIS) for prediction of roughness. Some of the methods relate the optical parameters retrieved from the image together with details about the machining conditions that produce the surface. Some methods utilize the surface information alone for correlating the stylus roughness. However, most of the techniques were able to predict surface roughness with reasonable accuracy.

2.4 STUDIES ON SURFACE EVALUATION

The effect of the lighting on the rotating components was studied by Gupta and Raman (2001). Experiments were conducted with and without lighting for different rotational speeds of turned components. It was found that the ambient lighting did not affect the optical surface parameter. Moreover, the rotation of the spindle did not have any effect on the roughness parameter and hence, concluded that this technique can be employed for online application.

Luk et al (1989) studied the effect of grazing angle of the light source and the illumination distance on the optical roughness parameter for different materials. It was found that the optical roughness parameter R1,
estimated from the images of the specimen immersed in cutting oil, had reasonable correlation with stylus roughness.

The histogram of five specimens of different roughness were studied by Hoy and Yu (1991). It was shown that the spread and mean value of the distribution increased, while the height decreased with increase in roughness.

In machine vision studies, if the component is kept inclined during imaging, there is a possibility of getting disturbed information. Hence, Priya and Ramamoorthy (2007) applied a shadow-removal algorithm on such deliberately inclined surface and improved the quality of evaluation. The correlation coefficient between the stylus roughness value and optical parameter increased after removing the shadows in the image.

Kumar et al (2005) improved the image by digital magnification. A cubic convolution algorithm was employed to achieve the digital magnification. An edge crispening mechanism was used to improve the edges after magnification. It was shown that the optical roughness value \( G_a \) for the magnified and improved images had a better correlation with the stylus roughness, indicating its effectiveness for surface roughness measurement.

2.5 SCOPE AND OBJECTIVES OF THE STUDY

From the literature review, it can be understood that machine vision is one of the field, where a lot of research activities are carried out to explore its capabilities in engineering application. Machine vision is largely employed in automated environment for part identification, classification or inspection. Though machine vision is successful for inspection of the surface for
identifying the shape, size, defects in IC chips, labels, etc., practical use of machine vision for surface roughness estimation is yet to find wide acceptance.

Many research works are reported in the application of machine vision for surface roughness studies. The review of the works indicates that different optical parameters can be retrieved from the image and correlated with the surface roughness measured by the stylus instrument. Those parameters can distinguish surfaces of different roughness. But, none of the parameters are identified as unique in the quantification of roughness. Moreover, the applicability of these parameters for different surface roughness is not discussed. A comparative study of these parameters on different roughness can provide useful information for the selection of the image-based parameter for analysis. Hence, in this study rough surfaces are generated under various conditions of machining for different materials. A comparative study is made on the different parameters estimated from these surface images.

In the machine vision studies, only the images of the surface are used for evaluation and there is no physical contact of the component. Hence, capturing the image of the surface at proper position of the work piece, camera and lighting are most important. Studies on surface evaluation have reported different methods of capturing the surface with different type of lighting arrangements. As the lighting arrangements influence the light scattering pattern and hence, the image captured, the study of the effect of these variables on the image can give more information for improving the accuracy of surface roughness prediction. In this aspect, the effect of the lighting conditions on one of the image-based parameter is analysed and a model is established to determine the surface roughness.
Advances in the image capturing hardware and the fast computational speed of personal computers (PCs) are leading to better processing and analysis of the image. New methods are adopted in the field of image processing to improve the information content of the image. In surface roughness evaluation using machine vision also, there is a need for better estimation of the surface roughness from the images. Hence, those new techniques that are employed in image processing can be applied to surface image and the possibility of estimating the surface roughness more precise can be explored.

2.5.1 Objectives of the Study

Based on the literature review and the discussion made, this research work on the study of surface roughness evaluation using machine vision is carried out with the following objectives.

- To make a comparative study of the different optical parameter retrieved from the images of the surface prepared under different machining conditions and find their application in surface roughness studies.
- To develop a program/software that can be used for retrieving the various optical roughness parameters from the image.
- To study the influence of lighting conditions on the optical roughness parameter on different materials and different roughness, by capturing the surface with different position of the light.
• To develop a model from the experimental data for the purpose of verifying the observations made on the study of the lighting conditions.

• To apply the different edge-enhancing image processing operation on the images and find the effect on the optical parameter. To find the suitable edge operation that gives the best result.

Figure 2.5 shows the scheme of investigation done for making the study on the surface evaluation using machine vision.
Figure 2.5 Scheme of investigations