A SYSTEMATIC METHODS OF MEASURING SURFACE ROUGHNESS BY IMAGE PROCESSING TECHNIQUE

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Abstract—A new method of surface roughness detection based on image processing technique is proposed in this paper. The developed vision system uses a CCD camera for scanning gray-scale images from an area of the machined workpiece. This images were analysed with digital image processing system. Some new optical roughness parameters were derived from the images based on their histograms and Optical objects of machined surface. As most useful were a number of dark objects of the image and coefficient of variation of the histogram of inspected surface.Surface roughness parameters are measured based on gray level co-occurrence matrix(GLCM) .In our proposed system we implement the image through histogram based segmentation and contrast method analysis. The material smoothness and roughness evaluated through pixel distance calculation of two points in image and analyze the result in micron based conversion.

Keywords—Surfaceroughness,CCDcamera,contrast method,GLCM

INTRODUCTION

Surface roughness evaluation is very important for many fundamental problems such as friction, contact deformation, heat and electric current conduction, tightness of contact joints and positional accuracy. Therefore, surface roughness has been the subject of experimental and theoretical investigations for many year. Many techniques have been developed for measuring surface finish ranging from the simple touch comparator to sophisticated optical techniques . In recent years, the advent of high-speed general-purpose digital computers and vision systems has made image analysis easier and more flexible. Computer vision techniques have been used for measuring surface roughness by many researchers. The term texture analysis is considered a basic issue in image processing and computer vision; therefore, it has been an active research topic for more than three decades. Many image processing techniques were employed to extract texture features from captured images in various applications Generally, texture analysis techniques can be grouped into three large classes: spectral, structural and statistical. Spectral techniques are based on the autocorrelation function of a region or on the power distribution in the Fourier transform domain in order to detect texture periodicities.

RELATED WORK

In[1],authors have proposed a roughness measurement by optical method. A surface roughness measurement technique, based on an optical method using a computer vision system, was investigated for applicability to in process monitoring of surface quality. The developed vision system uses a CCD camera for scanning gray-scale images from an area of the machined work piece. This images were analysed with digital image processing system. Some new optical roughness parameters were derived from the images based on their histograms and optical objects of machined surface.

In[2],authors have proposed a roughness measurement by ultrasonic method. Measurement of surface roughness irregularities that result from various sources such as manufacturing processes, surface damage, and corrosion, is an important indicator of product quality for many nondestructive testing(NDT) industries. Components and structures dimensioned from microns to centimeters can be found in semiconductors, data storage, microstructures and sensors, but also in precision manufacturing and engineering for automotive and aerospace industries.

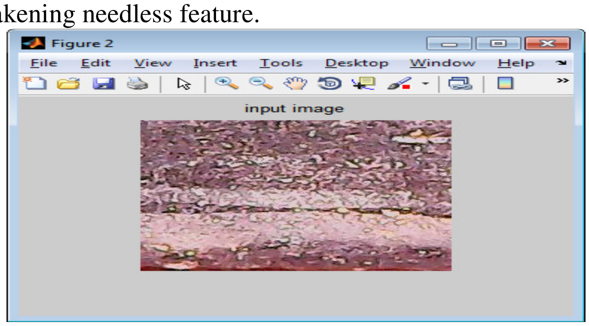
In[3],authors have proposed a surface roughness by histogram equalization. In recent years, the advent of high-speed general-purpose digital computers and vision systems has made image analysis easier and more exible. Images of surfaces captured using vision systems can be used to identify surface texture.

In this paper, a new method, called the best grey level histogram (BGLH), is introduced to get the most accurate image of a surface for the purpose of surface texture assessment. In recent years, the advent of high-speed general-purpose digital computers and vision systems has made image analysis easier and more exible. Images of surfaces captured using vision systems can be used to identify surface texture. In this paper, a new method, called the best grey level histogram (BGLH), is introduced to get the most accurate image of a surface for the purpose of surface texture assessment.

In[4],authors have proposed a roughness measurement by stylus. Recent work has shown that computer vision has real potential when applied to the automated measurement of engineering component silhouettes, internal contours and profiles. The present study considers the detailed examination of surface textures using the 3D data arrays which are available using this vision system. Progress has been made towards establishing a model of texture based on vision data and it has been shown that a parameter based on both amplitude and space features could provide an additional control for use in on-line automated inspection of manufactured components. Corresponding stylus data has been employed as the basis for comparison in the current evaluation process. In the field of tribology the automated examination of a wear track using computer vision has demonstrated that the approaches can be integrated so as to provide full information about the overall dimensions, area and texture of a wear scar.

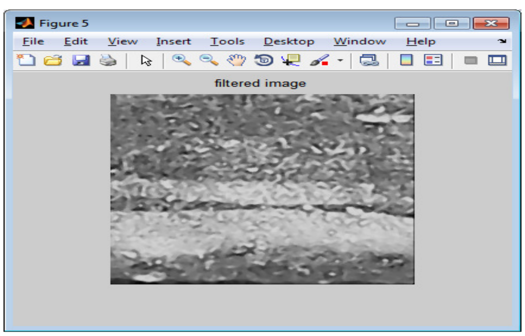
IMAGE PRETREATMENT

In general, due to various constraints and random interference, the images acquired by imaging system can' t be used directly in detection system, furthermore, image pretreatment such as gray scale correction and noise filtering, etc. must be taken on the original image in the initial stages of visual information processing. The image pretreatment method used mainly is taking appropriate transformation to the image according to specific needs, and giving prominence to useful features of the image selectively as well as removing or wakening needless feature.



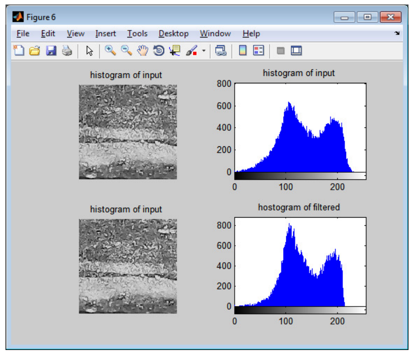
MEDIAN FILTERING

Median filtering is a nonlinear processing technology. It is a neighborhood operation similar to convolution, while the calculation is not weighted summation but sorting the pixels in the neighborhood by gray scale level,and then selected the intermediate value of the group as the output pixel value. Selection of median filtering function window is more important as it directly influences the effect of noise removing. By testing the filtering effect of window function 3 x 3, 5 x 5, 7 x 7, median filter 3 x 3 is chosen because that the filtering effect through window 3 x 3 is better than another two.



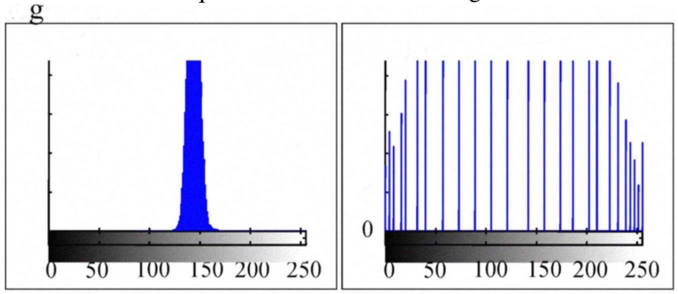
HISTOGRAM EQUALIZATION

Histogram equalization, also known as gray scale equilibrium, is a gray scale enhancement method, the objective of which is to convert the input image through point operation to the output image which has the same pixel points in each gray scale level. All gray scale levels of images after equalization processing appear with same probability, while the entropy of the image and the quantity of information it contains both are maximum, and it is beneficial to the further extraction of image features. For discrete images, the conversion formula of
Histogram equalization is:



$$D_B = \frac{D_{Max}}{A_0} \sum_{i=0}^{D_A} H_i$$

Where DB is the gray scale of output image, DA is the gray scale of input image, Hi is the pixel numbers of gray scale level i, DMax is the maximum gray scale value of the image (it is 255 to gray scale image).
Comparison of image histogram before and after equalization is showed in figure



a Histogram before equalization

b Histogram after equalization

CONTRAST METHOD

The speckle pattern images and their surface roughness Ra values, which are used to build calibration relationship curve for measure surfaces. According to, speckle can only be described by statistics and under ideal conditions. Ideal conditions include the same degree of roughness of a surface, allowing the speckle to develop fully, and perfect Gaussian beam statistics, and an air tight environment. The first –order statistics of speckle concern deviation from point to point. The assumption can be made that the standard deviation of intensity(σ) is equal to the mean of intensity <I> .

Where:

$$< I > = \frac{I_1 + I_2 + I_3 + \ldots\ldots + I_n}{n}$$

And

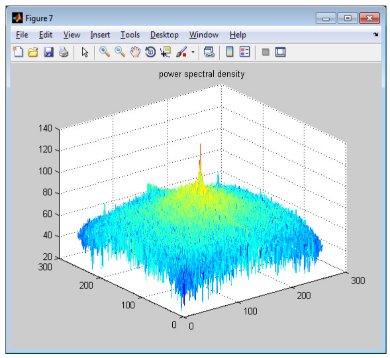
$$\sigma = \sqrt{< I^2 > - < I >^2}$$

In reality, the standard deviation is often less than the mean intensity[12]. The speckle contrast (C) usually defined as the quotient of standard deviation divided by the mean intensity[13,14]

$$C = \frac{\sigma}{\langle I \rangle}$$

POWER SPECTRAL DENSITY

Power spectral density function (PSD) shows the strength of the variations(energy) as a function of frequency. In other words, it shows at which frequencies variations are strong and at which frequencies variations are weak. The unit of PSD is energy per frequency(width) and you can obtain energy within a specific frequency range by integrating PSD within that frequency range. Computation of PSD is done directly by the method called FFT or computing autocorrelation function and then transforming it.



PSD is a very useful tool if you want to know frequencies and amplitudes of oscillatory signals in your time series data. For example, let assume you are operating a factory with many machines and some of them have motors inside. You detect unwanted vibrations from somewhere. You might be able to get a clue to locate offending machines by looking at PSD which would give you frequencies of vibrations. PSD is still useful even if data do not contain any purely oscillatory signals. For example, if you have sales data from an ice-cream parlor, you can get rough estimate of summer sales peak by looking at PSD of your data. We quite often compute and plot PSD to get a "feel" of data at an early stage of time series analysis. Looking at PSD is like looking at simple time series plot except that we look at time series as a function of frequency instead of a function of time. Frequency is a transformation of time and looking at variations in frequency domain is just another way to look at variations of time series data. PSD tells us at which frequency ranges variations are strong and that might be quite useful for further analysis.

GRAY LEVEL CO-OCCURRENCE MATRIX

The gray level co-occurrence matrix (GLCM) has been defined by Haralick .The GLCM is two dimensional matrix with the same size as the number of grey levels in an image. For example, the images used in this paper have 256 distinct grey levels; therefore the GLCM is a matrix of size 256 * 256. It could be constructed by counting the number of occurrences of pixel pairs (base pixel and neighbor pixel), which have gray levels i; j and their position specified by a position operator Ps;d in the image. The position operator Ps;d describes two parameters for the pixel pairs: pixel pairs spacing (PPS) and pixel pairs direction (PPD). The GLCM could be calculated as symmetric or non symmetric matrices. For non-symmetric matrices, eight PPD could be used to calculate the matrices, which represent the eight directions of the neighbors to the base pixel, as shown in the lower left of Fig. In this work, the direction 0 means that the neighbor pixel lies to the right of the base pixel; similarly, the direction 90 means that the neighbor pixel lies above the base pixel, etc. Symmetric matrices have only four directions. for calculations: horizontal (0,180), vertical (90,270), and the two diagonals (45,225 and 135,315). The only difference between symmetric and non-symmetric matrices is that while the position operator $P_{s,d}$ is passed over the image for non-symmetric matrices, both the operators $P_{s,d}$ and $P_{s,(180+d)}$are simultaneously passed over the image for symmetric matrices. It shows the flowchart of the algorithm used to calculate the GLCM. It shows how to calculate the GLCM from a sample matrix using different position operators. It shows a matrix represents an image of size 7 ×7 contains six gray levels (0–5). It shows the calculated GLCM using a position operator $P_{1,0}$; which produces a non-symmetric matrix. The black cells indicate the main diagonal of the matrix. Fig. shows the calculated GLCM using a position operator $P_{1,(180+0)}$; i.e. for the horizontal direction, which produces a symmetric matrix.

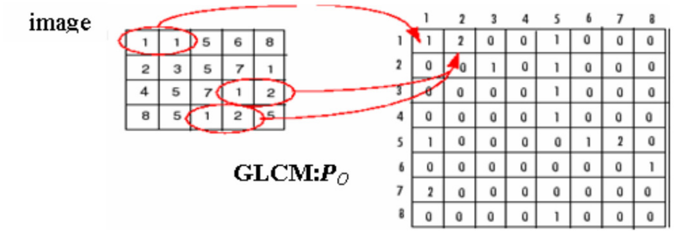


Fig:4

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R = sum(sum(GLCM));
Norm_GLCM_region = GLCM/R;

Ent_int = 0;
for k = 1:length(GLCM)^2
if Norm_GLCM_region(k)~=0
Ent_int = Ent_int + Norm_GLCM_region(k)*log2(Norm_GLCM_region(k));
end
end
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CONCLUSIONS

In this paper, we have discussed about surface roughness measurement, which is one of the major challenges in industrial application. Surface roughness parameters are measured based on gray level co-occurrence matrix(GLCM) .In our proposed system we implement the image through histogram based segmentation and contrast method analysis. The material smoothness and roughness evaluated through pixel distance calculation of two points in image and analyze the result in micron based conversion.

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