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ANALYSIS AND ASSESSMENT OF SURFACE IMAGE TEXTURE MECHANISMS

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Abstract: Surface roughness is an important indicator of the surface quality of machined work pieces. In order to discover the functional relation between cutting parameters and surface roughness, this study is focused on four popular methods which include two novel methods suitable for industry tools and surface examination. The focal point of this paper is to compare and contrast the four popular schemes, and to provide the introspect relating to the suitability of method for the applications. We have focused on such mechanism to deal with surface texture in this paper these are , Multiresolution Texture analysis using Wavelet Based Gabor filters, Neural Network based Algorithm, In-Process Approach , On-line Measurement Method. The results form the experiments from each algorithm are being discussed with their pros and cons and an insight is presented for a prudent analogy. This study would aid to readers in finding an ideal way out to consider best method for factual information about the defects and surface cracks in the machined tools or in any industry equipments.

Keywords: Texture, retrieval, roughness, vision-based, work piece, classification.

INTRODUCTION

Texture analysis refers to a class of mathematical procedures and models that illustrate the spatial variations within imagery as a way of extracting information. Texture analysis is one of the most vital techniques used in the analysis and interpretation of images, consisting of repetition or quasi repetition of a few fundamental image elements. Texture has so many different dimensions and no single method of texture representation that is adequate for a variety of textures for information retrieval. Texture analysis is a major step in texture classification, image segmentation and image shape identification tasks. Image segmentation and shape identification are typically the preprocessing steps for intended or object recognition in an image. There are three prime issues in texture analysis, i.e. texture classification, texture segmentation and shape recovery from texture and are very frequently needed in medical textile and big manufacturing industries for tool examination. Texture analysis has been used in a range of studies for recognizing synthetic and natural textures [1]. However, the number of studies on performance assessment of various methods remains questionable. Previous studies have either compared too few texture methods or on small number of samples for any meaningful conclusion. This elevates enough motivation to classify and analyze popular mechanisms which would explain extensively the textures in images [2]. The local image region, statistics or property that is repeated over the textured region, is called a texture element or texel. It must be noted that the texture has both local and global meaning, i.e., it is characterized by invariance of certain local attributes that are spread over a section of an image.

Analysis of texture requires the identification of proper attributes or features that differentiate the textures in the image for segmentation, classification and recognition. Texture analysis is a classical image processing topic that has received a lot of attention in the past decades. It still does because the correct characterization of texture in an image is of fundamental importance in many applications: medical, computer vision mechanisms have provided a number of texture analysis techniques with plenty of satisfactory results. The algorithms evolved so far in the reviews had been continuously upgraded in order to increase measuring precision; they are not efficient enough used in automated measuring systems, due to the fact that the stylus must make contact with the measured surface and also due to the very long time of measurement or lack consistent reading. Thus there is need to upgrade the methods which would focus on non contact images retrieval schemes [1, 5].

EXISTING POPULAR ALGORITHMS FOR IMAGE TEXTURE ANALYSIS

Multi-resolution Texture analysis using Gabor Filters:

This method describes an image retrieval technique based on Gabor texture feature. Texture is an important feature of natural images. A variety of techniques have been developed for measuring texture similarity. Most techniques rely on comparing values of what are known as second-order statistics calculated from query and stored images. These methods calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity or periodicity, directionality and randomness. Alternative methods of texture analysis for image retrieval include the use of Gabor filters and fractals [3]. Gabor filter wavelet is widely adopted to extract texture features from the images for image retrieval and has been shown to be very proficient.

This algorithms has shown that image retrieval using Gabor features outperforms that using pyramid-structured wavelet transform (PWT) features, tree-structured wavelet transform (TWT) features and multiresolution simultaneous autoregressive model (MR-SAR) features. Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction.

Expanding a signal using this basis provides a localized frequency description, therefore capturing restricted features or energy levels of the signal. Texture features can then be extracted from this group of energy distributions. The frequency and direction tunable property of Gabor filter makes it chiefly useful for texture analysis. Experimental evidence on human vision supports the idea of spatial-frequency (multi-scale) analysis that maximizes the simultaneous localization of energy in both spatial and frequency domains [4]. Currently, most techniques make an unambiguous or implied hypothesis that all the images are captured under the same orientations. In many practical applications such as image retrieval, object recognition such an assumption is unrealistic. Some other techniques carry out rotation normalization, but they are complex and computationally demanding. This method proposes a rotation normalization method that achieves rotation invariance by a circular shift of the feature elements so that all images have the same dominant direction.

Gabor filter (wavelet):

For a given image $I(x, y)$ with size $P \times Q$, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x,y) = \sum_s \sum_t I(x-s, y-t)\, \psi^*_{mn}(s,t)$$

where, *s* and *t* are the filter mask size variables, and ψ^*_{mn} is the complex conjugate of ψ_{mn} which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet:

$$\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] \cdot \exp(j2\pi Wx)$$

where *W* is called the modulation frequency. The self-similar Gabor wavelets are obtained through the generating function:

$$\psi_{mn}(x,y) = a^{-m}\psi(\tilde{x}, \tilde{y})$$

where *m* and *n* specify the scale and orientation of the wavelet respectively, with $m = 0$, 1, …*M*-1, *n* = 0, 1, …, *N-1*, and

$$\tilde{x} = a^{-m}(x\cos\theta + y\sin\theta)$$

$$\tilde{y} = a^{-m}(-x\sin\theta + y\cos\theta)$$

where $a > 1$ and $\theta = n\pi/N$.

The variables in the above equations are defined as follows:

$$a = (U_h/U_l)^{\frac{1}{M-1}},$$

$$W_{m,n} = a^m U_l$$

$$\sigma_{x,m,n} = \frac{(a+1)\sqrt{2\ln 2}}{2\pi a^m (a-1) U_l},$$

$$\sigma_{y,m,n} = \frac{1}{2\pi \tan(\frac{\pi}{2N})\sqrt{\frac{U_h^2}{2\ln 2} - (\frac{1}{2\pi\sigma_{x,m,n}})^2}}$$

In this implementation, the following constants as commonly used in the literature: *Ul= 0.05, Uh=0.4,* s and t range from 0 to 60, i.e, filter mask size is 60x60.

Texture representation and retrieval in Gabor scheme:

This section describes texture representation based on Gabor transform, texture similarity calculation and rotation normalization. After applying Gabor filters on the image with different orientation at different scale, an array of magnitudes is obtained.

$$E(m,n) = \sum_x \sum_y |G_{mn}(x,y)|,$$

$$m = 0, 1, \ldots, M-1; n = 0, \ldots, N-1$$

These magnitudes represent the energy content at different level and orientation of the image. The main purpose of texture-based retrieval is to find images or regions with same texture. It focus on images or regions that have homogenous texture, therefore the following mean and standard deviation of the magnitude of the transformed coefficients are used to symbolize the homogenous texture feature of the region.

$$\mu_{mn} = \frac{E(m,n)}{P \times Q}$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (|G_{mn}(x,y)| - \mu_{mn})^2}}{P \times Q}$$

A feature vector **f** (texture representation) is created using mean and standard deviation as the feature components. Five scales and 6 orientations are used in common implementation and the feature vector is given by:

$$\mathbf{f} = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots, \mu_{45}, \sigma_{45})$$

Annotations:

The application field of this method lies in the rock and metal/tool industry. The surface inspection by image analysis is beneficial in the quality control of the tool surfaces. It is fast and precise compared to traditional visual methods. Using Gabor wavelet scheme the retrieval algorithm is rotation invariant. The global texture features are extracted from the entire image, the extracted texture features are then used to measure the similarity between images. This method is most useful if the entire image or main part of the image has a uniform texture. In reality, an image may be considered as a mosaic of different texture regions. It is further proposed to incorporate texture segmentation along with scale invariance approach.

Neural Network Based Surface Roughness Algorithm:

Supervised neural network was developed in this study for the prediction of surface roughness in end milling process and its performance was tested. The network used in method is back propagation neural network (BP) with log sigmoid transfer function in hidden layers and linear transfer functions for the output layers[6].

The neural network architecture used in this study is shown in Figure 1. It was designed using MATLAB Neural Network Toolbox [7]. The network consists of one input, two hidden and one output layers. Hidden layers have 15 neurons each, whereas input and output layers have three and one neurons, respectively. Neurons in the input layers correspond to cutting speed (v_c), feed (f) and axial depth of cut. Output layer corresponds to surface roughness (Ra).

Before the ANN can be trained and mapping learned, the experimental data was processed into patterns. So Training, validation and testing pattern vector had been created before the ANN was trained. Each pattern was formed with an input condition vector.

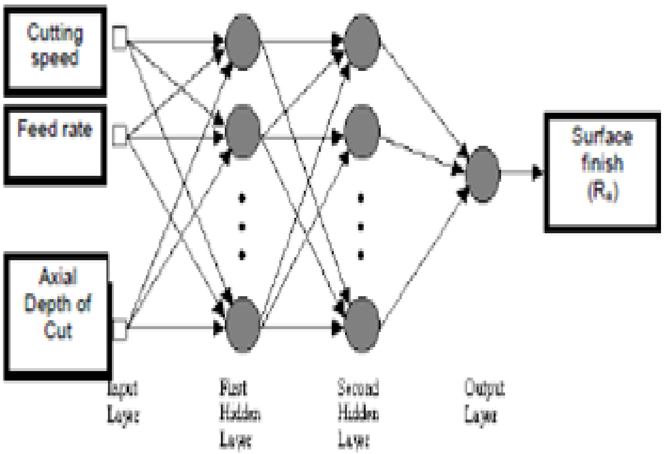

Figure 1. Model Development and Training the ANN model

$$Input_i = \begin{bmatrix} CuttingSpeed \\ FeedRate \\ AxialDepthofCut \end{bmatrix}$$

And the corresponding target vector,

$$Target_i = [SurfaceRoughness]$$

The back-propagation learning algorithm was used for training the network. For training the network, the TRAINLM function of MATLAB was employed which works on back propagation algorithm. These algorithms iteratively adjust the weights to reduce the error between the experimental and predicted outputs of the network [8]. TRAINLM updates weights so as to minimize the mean square error (MSE) between the network prediction and training data set. Based on the data set surface roughness can be computed.

***Annotations* :**

The multilayer network with two hidden layers having 15 log sigmoid neurons trained with "TRAINLM" algorithm was found to be the optimal network for the model developed in this study [7]. A good performance was achieved with the neural model as the error between the model prediction and experimental values ranging from 1.07% to 8.3%. The ANN model can now be used to analysis and predict the surface roughness for dissimilar cutting conditions. The surface roughness can be further optimized by coupling this ANN model with Genetic Algorithm or any other optimization methods. Similar ANN model can also be developed to envisage other process parameters such as cutting force, tools and machine parts investigation.

An In-Process Approach:

This approach is a new in its kind where in it employs a machine vision system for evaluating the surface roughness of the turned components by image processing and backlight technique as shown in figure 2. The surface roughness values obtained by the image processing technique and the traditional stylus probe method are then compared. The comparison results show that the proposed method gives more precise and reliable results which differ from the conventional stylus method. Since the proposed method is a non contact method it can be incorporated for in-process examination of the components without damaging the machined surfaces and also facilitates a complete inspection of the components in a small duration.

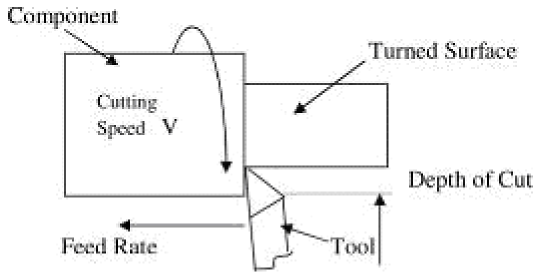

Figure 2: An In-Process Approach to Evaluate Surface Roughness of Turned Components

Turning is a generally used machining process in which material is removed using a single-point cutting tool on to a rotating cylindrical component. Material removal takes place in the form of chips from the surface of a rotating cylindrical component. The turned component produces some amount of surface roughness, which is an important parameter, which influences its service performances such as friction, lubrication, wear, thermal resistance, electrical resistance, fluid dynamics, noise and vibration Turning process is shown in Figure 2. A variety of parameters like cutting speed, feed rate, depth of cut , machine tool, cutting tool geometry, and component material all have an influence on the achievement of desired product quality and surface roughness values at an suitable cost.

Many experts have analyzed the influence of cutting parameters in turning and they have stated that higher surface roughness values in highly ductile material at higher cutting speed increase the affinity to form a large and unstable built-up edge and cause poor surface finish. Hence, it is important to measure, monitor, and control the surface roughness while the components experience machining. Traditional method of surface roughness measurement in industries is by stylus method. The major drawback of using this method is that it requires straight physical contact, which restrictions the measuring speed. In addition, the instrument readings are based on a limited number of line samplings, which may not represent the real characteristics of the entire surface Rajneesh Kumar (2005). Machine vision is tried as a substitute for stylus instruments for surface roughness measurement. Many investigators have used optical and image-processing techniques as an alternative.

On the other hand, in rough surface light is scattered in all the directions so they have introduced a parameter called the optical roughness indicator to determine the surface roughness of grinded materials. This parameter indicates the change in size of the illuminated area which is captured by a CCD camera. The roughness measurement is based on the speckle pattern caused by a laser beam. The statistical parameters are derived from the grey-level intensity histogram of components of grinding, milling, and shaping. The mean value of the intensity distribution is correlated with the Ra value obtained from stylus instrument to conclude the surface roughness of the machined components. Many researchers have used Ga, an index of the arithmetic average of the grey level of the image. Its Ga value is correlated with the actual surface roughness value Ra obtained by stylus instrument to obtain an equivalent Ra using machine vision system. The arithmetic average of the grey level is obtained from Eqs. (1) and (2):

$$Ga = (\Sigma(|g1 - gm| + |g2 - gm| + |g3 - gm|\square + |gn - gm|))/n$$

$$gm = (\Sigma(g1 + g2 + \square + gn))/n \qquad (2)$$

where n is the number of sampling data, g1, g2, …, gn the grey-level values of a surface image along one line and, gm the mean of the grey values in the line of selection. The association among the specular reflectance, total reflectance and diffuse reflection has been investigated. Most of the existing vision-based methods discussed by the researchers including the authors have used a front lighting system.. Most of the methods available are worked in the laboratory conditions and controlled environment which may not readily suitable for shop floor inspection because of the varying lighting conditions. But this method, illustrates an alternative method for measuring the surface roughness of turned parts using image processing and back lighting techniques is proposed. The setup is much easier to construct in any place of the shop floor and will not be affected by the ambient light conditions. Step by step procedure for evaluation of surface roughness by\ image processing:

Step 1: Preparation of Specimen
Step 2:CCD and Lighting correction
Step 3: Image Capturing and Storing
Step 4: Pocess of Image Filtering
Step 5: Image Binarization
Step 6: Edge Detection
Step 7:Location of the Best fit line
Step 8: Estimation of Surface Roughness is done.

Annotations:

This novel technique using machine vision system and back light method is used for evaluating the surface roughness of machined components. Cast iron specimens are turned under different machining conditions to obtain different surface roughness values. The machine vision system captures the magnified profile edge image of the specimen while it is being turned and stores it in the computer. In-house developed software computes the surface roughness directly from the profile image of the specimen. The advantage of using back lighting system is that it is not influenced by lighting conditions of the industrial environment. The accuracy of the proposed method was compared with stylus method through several experiments. A comparison graph drawn between the proposed method and stylus method showed the correlation coefficient (*R2*) values close to one and the percentage error calculated shows a maximum variation of + 12 %.

On-Machine Measurement of Large-Scale Work piece Based on Machine Vision:

On-machine measurement(OMM) based on machine vision is the recent sizzling research topic because of coordinate measuring machine(CMM) measurement requires significant resources in operating time as well as cost constraints. This method aims to develop an OMM method with a manipulator and industry camera. First, an on-machine calibration method of industry camera based on image sequence is studied. A set of monocular stereo system was established on the NC milling machine. A calibration target was designed to meet the requirements of finding enough and accurate correspondence relationship. Calibration method is illustrated involving taking image sequence, detecting the position of the calibration board and the marking points, finding the marking points' correspondence with their projection, determining the camera parameters through optimization algorithm. Accuracy of calibration shows that choosing 10 calibration images is appropriate for on-machine calibration. Second, image mosaic method for on-machine measurement of large-scale workpiece is investigated. Image sequences were acquired by controlling the moving of working table. Image mosaic of large-scale work piece was realized with high precision. Size measurement result proved the effectiveness and high efficiency of this OMM system.

On-machine calibration with Image sequence:

Recent trend is toward convenient and precise calibration methods for vision measurement system in industrial field, which is the focus of this method. This paper intends to introduce a on-field calibration approach on the basis of image sequence, which can not only be used in the lab environment, but also help with the parameter calibration for movable monocular camera of NC machine in the workshop.

Target Selection:

In order to find enough 3D points, objects and signs whose features are easily extracted, such as circular points and marks, are usually positioned at a know location. In general cases, it is enough to measure an object accurately with the position of a reference object relative to the camera known. There is no need to clarify the position of such object in the coordinate system [9, 10]. Therefore, the camera can be calibrated with a movable, previously measured calibration board whose size is known. In order to fulfill the second requirement, it is necessary to determine the correspondence between the known points in the world coordinate system and their projections in the images which is very difficult. Therefore, in general, the structure of the calibration board should make the process of determining the correspondence as simple as possible. As shown in Figure 3, it is a self-designed planar target with a circular marking point.

It is printed by laser printer of high quality and then stick on the back of the plexiglass panel of high flatness. Secondly, putting a small direction mark in the corner of the rectangular bounding box can make the camera calibration algorithm work out the only direction of the calibration board. Thirdly, putting circular mark on the surface of the calibration target will help to extract the coordinates of the central point of the circle accurately. Finally, all the circular marking points are ranked as rectangular array, which therefore makes it simpler for the camera calibration algorithm to retrieve the pixel coordinates of the corresponding pixel points. Major design parameters are: a black square with length and width measuring 100mm; a right angled triangle with the length of the right-angle side measuring 12.5mm; two chord crest located at the line of centers of the horizontally and vertically first marking points; 6.25mm diameter black marking points equally distributed in 7*7 array format with the center distance measuring 12.5mm These chief parameters are compiled as a 'caltab.descr' file which is temperately stored in the work space of the computer for further use.

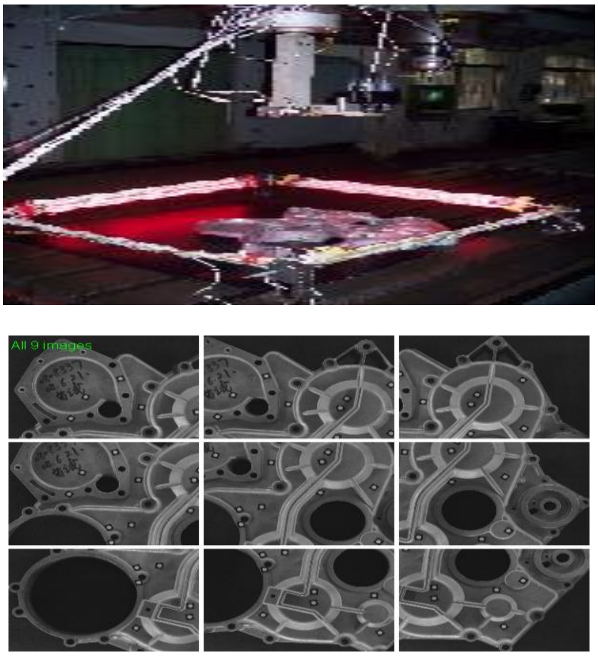

Figure 3: On-machine vision measurement and tool surface Images

Annotations:

In this mechanism, an OMM system was developed for computing the large-scale work piece on the machine tool. An on-machine camera calibration method based on image succession. The problem of degeneracy in calculating the camera parameters is responsible for using calibration image sequence. The accuracy of calibration parameters is immensely improved as the number of calibration images raised. Since the accuracy of calibration become steady after the number of calibration image increases to 10. Therefore, choosing 10 calibration images is an appropriate approach. Image pair configuration, feature extraction and the projection matrix calculation methods of image were analyzed and used. With the support of the feed movement of numerical control machine, it can also realize image mosaic and on-machine vision measurement of large-scale work piece with high precision and high competence below proper lighting.

CONCLUSION

In this paper we have discussed four popular texture analyzing Mechanisms with their traits. It has been established that wavelets based Gabor method is good for uniform texture surfaces. The artificial neural network (ANN) method focuses mainly on prediction of surface roughness for dissimilar surfaces and cutting conditions. In-process approach mechanism envisage on direct profile image of the specimen on turned machine image texture analysis. On-machine method focuses on more practical perspective of measurement i.e. surface texture computations for a large-scale work piece with high accuracy and also with a higher precision. It has been shown that there is a correlation between the height of the roughness and the image grey levels, thus the estimation of surface roughness can be done in similar ways as texture analysis through all the methods discussed. As a futuristic view it is felt that mechanisms which can capture images in-line and by dynamic means would be in demand than static work piece based methods. It can be concluded that the methods of surface image texture processing is better than the methods using the stylus kind of measurement techniques , because it is faster , accurate and there is no contact between the measuring instrument and the surface.

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