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A REVIEW OF MACHINE VISION BASED EVALUATION OF SURFACE ROUGHNESS USING TEXTURE ANALYSIS TECHNIQUES

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ABSTRACT

Machine vision systems have the potential of replacing traditional methods used for inspection of surface quality. Surface finish is an important characteristic from operational, ergonomic and aesthetic aspects of quality. Machine vision systems can effectively extract texture of surface under inspection and evaluate its surface roughness. This non-contact type of measurement technique is efficient, reliable, fast, robust and cost-effective in capturing surface quality. In this paper, recent advances in machine vision based evaluation of surface roughness using texture analysis techniques and predictive modelling methods are reviewed. Image texture analysis techniques used by researchers for this purpose are mainly categorised into statistical approaches and filter based approaches in spatial and frequency domain. The image textures extracted using these techniques are then used for evaluating surface roughness using various prediction models. A comprehensive study of these techniques is presented in this paper that throws light on the current state-of-technology.

***KEYWORDS*: Machine Vision, Surface Roughness, Texture Analysis.**

1. INTRODUCTION

Machine vision systems provide an effective contactless method for analysing texture of surface under inspection and detecting defects if any. The technique is based on the principle that an image is a two dimensional image-intensity function characterized by illumination which is dependent on the light source and reflectance which is dependent on the characteristic of the surface of object [1]. Using these image intensity values of various pixels in an image, surface texture parameters can be deduced which are useful in characterising surface texture.

Texture analysis techniques most widely used by researchers for measurement of surface roughness include statistical and filter based approaches. Texture analysis techniques deduce certain texture parameters by analysing the image of surface under consideration and these parameters are then used for evaluating surface roughness using various predictive modelling methods. This approach is capable of capturing two-dimensional roughness data as compared with one-dimensional data based on line sampling provided by traditional stylus based surface tester.

2. TEXTURE ANALYSIS APPROACHES

Materka and Strzelecki (1998) classified texture analysis techniques in four categories namely structural analysis, statistical analysis, model-based analysis and transform based analysis [2]. Structural approach represents texture with primitives and a hierarchy of their spatial arrangements. Statistical approach represents texture using properties governing distribution of gray levels and relationships between grayscale levels of the image. Whereas model based approach represents texture with the help of fractal and stochastic models whereas transform approach applies filters in spatial or frequency domain and compute energy of responses in order to characterise texture.

Xie (2008) classified texture analysis techniques used for detection of surface defect into statistical technique, structural technique, filter based technique and model based technique. Statistical methods for surface defects detection include histogram properties, coloured and gray level co-occurrence matrix, local binary patterns, other gray-level statistics and autocorrelation whereas filter based approaches include spatial, frequency and spatial-frequency domain transformations. It is also said that statistical methods are suitable for patterned textures whereas filter based methods are appropriate for analysis of random textures. Also model based methods can capture both statistical and structural texture properties in an image [3]. Among these approaches, statistical and filter based approaches are most commonly used for evaluating surface roughness.

3. EVALUATION OF SURFACE ROUGHNESS USING STATISTICAL METHODS

Statistical methods used for extraction of surface texture and evaluation of surface roughness include histogram properties and other gray level features, co-occurrence matrix and gray level co-occurrence matrix (GLCM).

3.1. Histogram Properties and Gray Level Statistics

Histogram Properties such as mean, standard deviation, range, median, kurtosis, skewness, energy, entropy effectively communicate first order statistical information related to pixels intensity values in an image [2]. Histogram comparison statistics can also be used to identify defective regions. First-order histogram based features are proved to be simple, low level and cost effective in texture analysis [3].

Kindi and Shirinzadeh (2007) used statistical measures for evaluating surface roughness parameters with the help of vision based data. Experimentation and analysis for prediction of surface roughness were carried out with three different techniques: stylus based measurement, machine vision based measurement with intensity topography compatible (ITC) model and machine vision based measurement with light-diffuse data model. Overall accuracy was within 15% of deviation from stylus based values except for skewness parameter. The amplitude parameters, spacing parameters and combined amplitude-spacing parameters specially meant for assessment of surface roughness proved to give deviation lower than 6%. It was concluded that industrial 3D vision based surface roughness measurement system can be developed based on these models and can be extended to relatively smoother surfaces with adequate image resolution [4].

Balasundaram et al. (2014) determined machine vision based amplitude, spacing and hybrid and bearing area curve roughness parameters on-line in dry turning of carbon steel AISI 1035. The effect of tool nose wear on surface roughness was studied by measuring average slope of profile peaks and valleys and relative length of the peaks. The values of surface roughness parameters were compared with stylus outputs and were found to be in good agreement. Average slope of profile peaks and their relative length demonstrated better correlation with the machining time and tool nose wear. Hence it was concluded that these parameters can be used with other statistical measures for surface roughness prediction [5].

Shivanna et al. (2014) evaluated 3 dimensional surface roughness parameters of Electro-discharge-machined (EDM) components with machine vision. 3D amplitude parameters such as roughness average, root mean square (RMS), peak-to-peak height, skewness, kurtosis, maximum peak height and maximum valley depth were determined using CCD camera and compared with the parameters captured by optical method using confocal Microscope. The values obtained by machine vision systems were in good agreement with those obtained by optical method [6].

Kumar et al. (2005) estimated surface roughness by varying speed, feed and depth-of-cut for various machining operations such as milling, shaping and grinding. Optical surface roughness value was calculated using sum of variations in gray levels from mean. Then regression analysis of optical values with stylus based measurement values was carried out for estimation of surface roughness. It was concluded that the method is more appropriate for machining operations that produce uniform, regular surface textures [7].

Kamguem et al. (2013) used gradient factor of surface derived from threshold equations by Otsu's thresholding method of conversion of gray image into binary image [8] and principle of average texture cycle that calculates average values of the cycle of [0 1] column-wise in the binary image as proposed by Zhang et al. [9]. The study showed that using this statistical approach, surface roughness features can be effectively estimated even without the knowledge of machining parameters [10].

Nathan Dhanapalan et al. (2014) used skewness, kurtosis, entropy, standard deviation and mean extracted from image to train multilayer back propagation artificial neural network (ANN) for estimation of surface roughness of end milled 6061 Al alloy components. ANN predicted values were in good agreement with stylus based values [11].

3.2. Gray Level Co-occurrence Matrix (GLCM)

Histogram statistics though being simple cannot completely characterise surface texture. Hence second order statistic known as co-occurrence matrix is used which estimates joint probability $P_{d\theta}(i,j)$ of two pixels, which are a distance d apart along a direction θ with values i and j [2]. Haralick (1979) suggested to consider $d = 1$ and $\theta = 0^0, 45^0, 90^0, 135^0$. Basic features extracted from GLCM such as angular second moment (energy), correlation, contrast, absolute value, maximum probability, inverse difference, entropy can be useful in determining texture [12]. GLCM can give reliable results only if sufficient number of graylevels is present in the matrix [3].

Wang et al. (2009) used GLCM based Fractal method for surface roughness evaluation for a fabric. Parameters such as contrast, homogeneity, dissimilarity, angular second moment, entropy, mean, variance and correlation were calculated from GLCM. It was concluded that GLCM based parameters can be good descriptors of textures and fractal dimensions have the ability to evaluate surface roughness [13].

Nathan et al. (2014) studied GLCM parameters for determination of surface roughness of AA6061 alloy in end milling operation. Images of milled surfaces for various combinations of speed, feed and depth-of-cut based on L27 orthogonal array were taken and their texture parameters including energy, contrast, homogeneity and correlation were determined using four GLCMs. Texture features and surface roughness measured using stylus method were then compared to establish their relationship. It was found that variations in contrast and surface roughness have similar trends and are irrespective of the orientations. It was also found that energy, correlation and homogeneity do not vary proportional to the surface roughness [14].

Gadelmawla (2016) investigated GLCM features and their relationship with surface roughness. Six texture features sum variance (SVAR), difference variance (DVAR), sum entropy (SENT), angular second moment (ASM), cluster shade (CSH) and sum average (SAVR) were found to be highly correlated to surface roughness [15].

Other statistical measures for texture characterization include local binary pattern (LBP) operator which uses gray level of centre pixel as a threshold for surrounding pixels and gives weighted sum of thresholded neighbouring pixels [16].

4. EVALUATION OF SURFACE ROUGHNESS USING FILTER BASED METHODS

Filter based approaches work on the principle of characterisation of texture based on filter responses for the image in spatial or frequency domain.

4.1. Filter Based Methods in Spatial Domain

Variation in intensity values of different pixels in an image, characterised by Eigen vectors and associated Eigen values can be a powerful technique to determine texture. The Principal Component Analysis (PCA) method can be used to characterise and distinguish between various images using these

Eigenvalues. However these Eigen filters are image dependent [3].

Bharati et al. (2001) used multivariate transformation of gray scale image followed by PCA to analyse surface texture. It was found that cumulative percentage sum of squares that was explained by first three principal components for good and bad surface samples were 99.36% and 99.20% respectively. Then, 2D scatter plots of PC score vectors were plotted and used for template matching by calculating mean sum of squares between two score spaces [17].

Jeyapoovan et al. (2013) used principal component analysis to classify machined-surface images into different classes of surface roughness. Six different specimens were prepared on milling by changing feed while keeping other parameters constant. The 2D normalized rectangular images were converted into 1D image intensity vectors for reference database. Then test images were classified into these six classes based on minimum Euclidian distance and Hamming distance from reference images. It was found that Hamming distances are smaller than Euclidean distances and the method can be adopted for other processes such as planing, EDM and grinding with larger databases for better accuracy [18].

Samtaş et al. (2014) used image processing and ANN for evaluation of surface roughness of face milled surfaces of carbon steel AISI 1040 and aluminium alloy 5083 using various tools, speeds, feeds and depths of cut. Binary images converted into column vectors for all test specimens were given to ANN as inputs and stylus based surface roughness value as output with various transfer functions and training algorithms with different number of neurons. It was concluded that the method gives sufficient measurement accuracy and can be adopted for various machining operations [19].

4.2. Filter Based Methods in Frequency Domain

Filter based approach in frequency domain for texture analysis includes Fourier transform, wavelet transform that represent an image in a space with its coordinates interpreting relation to the texture characteristics.

4.2.1. Fourier Transform

Fourier transform is based on an assumption that the texture is uniform in nature and represents an image as a summation of cosine (orthogonal) images. Fourier function F(u,v) is complex , having real part and imaginary part. It is represented by magnitude and phase calculated using equations (1) and (2) as follows.

$$\text{Magnitude} = \sqrt{\text{Real}(F)^2 + \text{Imag}(F)^2)^2} \quad \ldots (1)$$

$$\text{Phase} = \text{ATAN}\ \frac{\text{Imag}(F)}{\text{Real}(F)} \quad \ldots (2)$$

Magnitude represents the number of times a frequency component is present in the image and phase represents the location of frequency component in the image. Some important features extracted from Fourier Transform (FT) useful in determining surface texture are major peak frequency, central power spectrum percent, principal component magnitude squared, average power spectrum and ratio of major-to-minor axis [20, 21]. These parameters can be used to build prediction models based on optical or stylus based output values. It is suitable for components characterized by directional patterns with periodic, parallel feed marks. However it is unsuitable to predict surface roughness with irregular surface textures. Also Fourier transform lacks in spatial localization of features. Gabor filters are better in the aspect of spatial localization however have limited practical applications due to the fact that generally single filter resolution can not be used for localization of a spatial structure.

4.2.2. FFT Coupled with Artificial Neural Networks

Artificial neural networks can be effectively used in order to map various texture parameters extracted from image with surface roughness. The networks, inspired from biological nervous system, are trained until a set of inputs lead to specific target output. Such ANNs can then be used to evaluate roughness of any new surface under inspection.

Fadare et al. (2009) carried out 2D FFT to determine image texture features like major peak frequency, average power spectrum , central power spectrum percentage, principal component magnitude squared, ratio of major-to-minor axis and tool wear index. These parameters were defined as six neurons in input layer and optical roughness was defined as one neuron in output layer of feed-forward multilayer perceptron neural network. ANN predicted values and optical roughness values were found to be in good agreement. It was concluded that the method can be used for offline or online inspection of surface quality [20].

Palani et al. (2011) used ANN based on 2D FFT of images. Surface roughness features such as principal component magnitude squared, major peak frequency and average gray level were calculated using 2D Fourier transform of CNC end milled components. ANN was trained with back-propagation by feeding stylus based surface roughness value and these texture feature values. The ANN developed was capable of predicting surface roughness with 97.53% accuracy. [1].

Saric et al. (2013) compared performance of various neural networks (NN) in predicting surface roughness. The face milling operations were performed at various levels of speed, feed, depth-of-cut and cooling methods. Performance of various neural network training algorithms with different transfer functions (TF) and learning rules (LR) was compared based on root mean square error for learning and validation phase. The best results were obtained with the combinations of sigmoid as TF for all networks, delta as LR for back propagation NN and modular NN whereas normalized-cumulative delta as LR for radial basis function NN. It was concluded that artificial neural networks trained using machine vision texture parameters data can effectively predict surface roughness [21].

4.2.3. FFT Coupled with Neuro-Fuzzy Models

Neuro-fuzzy approach offers benefits of artificial neural networks coupled with fuzzy logic rules for complex scenarios. The approach uses expert neurons for generating fuzzy if-then rules.

Kumanan et al. (2006) used adaptive neuro-fuzzy inference system (ANFIS) and radial-basis function neural network using fuzzy logic (RBFNN-FL) for predicting surface roughness for end milling operation. Comparison of Root mean square errors for neuro fuzzy models with neural models showed that neuro fuzzy models were more accurate. Hence it was concluded that hybrid techniques have better computational efficiency [22]. Natarajan et al. (2012) ANFIS to accurately predict surface roughness of milled components using input parameters such as cutting speed, feed, depth-of-cut along with average grey level, major peak frequency and principal component magnitude squared extracted using 2D FFT [23]. Palani and Kesavanarayana (2014) used Ra, Ga, speed, feed and depth of cut as input parameters to neuro-fuzzy model to accurately estimate surface roughness [24]. It was observed that ANFIS based models provide better results than ANN models in terms of modelling and prediction accuracy. Hence they can be used for real time industrial surface inspection.

4.2.4. Wavelet Transform

Wavelet transforms (WT) prove to be better due to the fact that they allow representation of texture at most suitable scale by varying spatial resolution, also provide a wide range of wavelet functions for various applications [2]. In wavelet transform, all basic functions (wavelets) are scaled, shifted copies of a mother wavelet. Wavelet transform decomposes image into a set of independent spatially-oriented frequency channels such as HH, HL, LH, LL sub-images in one-scale. In subsequent analysis, each sub-image is further decomposed and then energy of each channel calculated as mean magnitude of wavelet coefficients can characterise the texture of an image.

Morala-Argüello et al. (2012) used WT to evaluate surface roughness classes using computer vision. Haar type 2D discrete wavelet transformation (DWT) was applied on images to extract approximate coefficients as well as horizontal, vertical and diagonal coefficients. Gray level means were determined from sub-images in most prominent directions of variations and were fed to multilayer perceptron ANN for discrimination into different surface roughness classes [25].

Srivatsa et al. (2016) estimated surface roughness using Haar wavelet packet transform and multilayer perceptron ANN for turned components. Speed, feed, depth-of-cut, mean, variance, skewness, kurtosis and standard deviation were given as input neurons and stylus based Ra value as output to the ANN. ANN Predicted values were found to be in good agreement with experimental values [26].

D. Nathan et al. (2016) used Haar type wavelet transform in order to extract texture parameters from four sub-images of an image and back propagation learning algorithm Lavenberg-Marquardt (LM) in feed forward ANN with single hidden layer and LOGSIG transfer function. Different energy features of approximation coefficients and horizontal, vertical and diagonal detail coefficients at level 1 and 2 were used to characterize surface texture [27].

Chang and Ravathur (2005) used discrete wavelet transform for finding prominent detailed channels with high energies, developing input energy vectors and building roughness prediction models using response surface methodology [28].

5. CONCLUSION

This paper presents an extensive review of various texture analysis approaches used for characterization of machined surfaces and prediction of their surface roughness using machine vision approach. Detailed discussion of various machine vision based texture parameters used by researchers is useful in getting a comprehensive list of parameters for further investigations and research.

Statistical and filter based approaches are most widely used texture analysis techniques for measurement of surface roughness. Histogram based first order statistical methods or second order GLCM methods provide simple, low level texture parameters. Filter based approaches in spatial or frequency domain can be effectively used to capture higher order texture information. Prediction models are then developed based on these parameters that map these texture parameters to surface roughness values measured using optical methods or stylus based methods. Efficiency of the models developed is highly dependent on proper selection and combination of texture analysis methods, texture parameters and prediction models. Highly efficient, robust and cost-effective prediction models for evaluation of surface roughness based on machine vision can potentially replace traditional contact-type methods.

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