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A Comparative Study to Assess the Effectiveness of Surface Texture Classification Algorithms

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Abstract— *Surface texture measurement plays a very important role in predicting the functional performance of the components. An attempt has been made in this paper, to assess the effectiveness of texture classification by Gabor filters and Tree Structured Wavelet Transform. The method is used successfully for inspecting surfaces made of Milling, Shaping, EDM and sandblasting processes. The proposed method uses a relatively low cost vision system for analyzing different textures. The method is non-contact, quick and finds application in inspecting components produced by computer integrated manufacturing. High classification accuracy is possible.*

Keywords-*Surface Textures; Process Identification; Texture classification; Image classification*

1. INTRODUCTION

The surface texture is important for many reasons including friction, wear, lubrication, contact with other parts, and the ability to hold coating. Hence there were many research attempts in the past for measuring surface texture. Several well-known roughness parameters are used to quantify surface texture Gadelmawla et. al.,2002[1]. The surface roughness parameters like Ra, is used to describe a surface. However, it is possible that two surface textures can have the same Ra, but their frictional characteristics could be different Menezeset. al.,2006[2].Thus complete understanding of surface texture is very much required for predicting the functional performance of the component. Surface texture produced on a component is governed by the manufacturing process. Also, the texture produced by every manufacturing process is unique. Hence, texture analysis assumes special significance. The proposed method of texture analysis uses a low cost vision system and is non-destructive and non-contact in nature.

Texture is generally used to characterize the surface of a given component and it is one of the main features used in image processing and pattern recognition. A discrete tonal feature on a digital image is a connected set of resolution cells all of which have the same or almost the same intensity. Texture is concerned with the spatial distribution of image intensities and discrete tonal features. When a small area of the image has a little variation of discrete tonal features, the dominant property of the area is grey tone. When a small area has wide variation of discrete tonal features the dominant property of that area is texture Haralick et.al. 1973 [3].

2. *APPROACHES TO TEXTURE ANALYSIS*

Much research has been done in the area of analyzing the human visual system and also in trying to simulate human vision as long as Machine vision is involved. Pickett in 1970[4] mentioned that some of the basic properties of the optical data which the visual system may measure include the various characteristics of elements (viz. size, shape, colour orientation), number or density of elements and arrangement of elements. The Visual features approximated in computational form were coarseness, contrast, directionality, line-likeliness, regularity and roughness. In 1978, Julesz [5] characterized the statistical and structural approaches as perceptual and cognitive respectively. Basically texture classification schemes can be classified into statistical, structural and multi resolution filtering methods.

2.1. STATISTICAL METHODS

The statistical methods extract a set of parameters (features) from a given image Devdas and Imbert 1984[6]. The parameters are then used as input features for classification using the techniques of statistical pattern recognition. The parameters were derived over space or frequency domain. There are different methods in statistical approach Weszca et al. 1976[7].

2.11. **The grey-level difference method** Haralick et al. 1973[3] estimated the probability density function for differences between picture function values.

2.12. **The spatial grey level dependence method** Haralick et al. 1973[3] estimated the joint grey level distribution for two grey levels at distance 'd', and an angle 'θ'. The grey level differences and joint grey level distributions are known as first and second order statistics respectively. The first order statistics are embedded in second order statistics as marginal density functions.

2.13.The grey-level run length method estimated the identical runs, where an identical run is defined as a set of connected pixels having the same grey level Galloway 1975[8]; Chu et al. 1990[9]. One of the characteristic aspects of texture is its spatial granularity (frequency content) and repetitiveness. Fourier Transform techniques are used to extract such information Lendaris and Stanley 1970[10].

The first and second order statistics (co-occurrence matrices) are the most commonly used statistical methods for texture discrimination Helstrom 1968; Haralick 1973[3]. One problem with the co-occurrence method is related to the need to define 'd' and angle 'θ', which would fully specify the method.

2.2 STRUCTURAL METHODS

The structural approach assumed that a set of primitive units can be identified. It then defined textures as a combination of such primitives according to different placement rules. There are two major problems with this approach. First it is not easy to identify the primitives. Secondly the patterns are repeated according to pre-specified rules and should allow us for a stochastic change in the replication process and the same should apply for the pattern themselves Haralick et. al. 1973[3].

A major stumbling block for the texture analysis problem is that of determining the appropriate size and shape of the area from which the textural features should be extracted Haralick 1973[3]. The area of the minimal texture in which the meaningful information can be extracted is known as the cell unit.

2.3 MULTI RESOLUTION FILTERING

There are a lot of similarities between multi resolution filtering techniques (e.g. Gabor Filtering) and human visual process. Gabor filtering is used to characterize the texture in spatial-frequency domain.
A two dimensional Gabor function A.C. Bovik 1990[11] is defined as

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x2}{\sigma_{x2}}+\frac{y2}{\sigma_{y2}}+2\pi jWx)] \quad (1)$$

Where, σx and σy are the standard deviations of the Gaussian envelopes along the x and y directions, Long F.et al.,2003[12]. Then a set of Gabor filters can be obtained by rotations and dilations of $g(x,y)$. Some of the limitations of the approach have been reported in Kiran et al. [13]. An attempt has been made in this paper to evaluate the effectiveness of texture classification by Gabor Filters and Tree Structured Wavelet Transform.

The following paragraphs highlight the theory and application of both the methods.

3 THEORY OF TREE-STRUCTURED WAVELET TRANSFORM

Wavelet transform, means the decomposition of a signal with a family of real orthonormal bases $\psi_{m,n}(x)$ obtained through translation and dilation of a kernel function $\psi(x)$.

$$\psi_{m,n}(x) = 2^{-m/2}\psi(2^{-m}x - n) \quad (2)$$

Where m and n are integers. Due to the orthonormal property, the wavelet coefficient of a signal $f(x)$ can be easily computed as follows.

$$c_{m,n} = \int_{-\infty}^{+\infty} f(x)\psi_{m,n}(x)dx$$

And the following formula

$$f(x) = \sum_{m,n} c_{m,n}\psi_{m,n}(x)$$

can be used to construct $f(x)$ from its wavelet coefficients. Wavelet $\psi(x)$ can be determined as follows. Scaling function $\phi(x)$, is defined which satisfies the two-scale difference Daubechies [14]

$$\phi(x) = \sqrt{2}\sum_k h(k)\phi(2x-k) \quad (3)$$

The wavelet kernel $\psi(x)$ is determined as follows.

$$\psi(x) = \sqrt{2}\sum_k g(k)\phi(2x-k) \quad (4)$$

Where

$$g(k) = (-1)^k h(1-k) \quad (5)$$

The coefficients $h(k)$ in (3) have to meet several conditions for the set of basis wavelet functions in (2) to be unique, orthonormal, and have a certain degree of regularity Strang [15]. Several different sets of coefficients $h(k)$ satisfying the above conditions can be found in the wavelet literature Daubechies [14], Daubechies[16], Mallat SG [17], Mallat SG [18].

The coefficients $h(k)$ and $g(k)$ play a very crucial role in a given discrete wavelet transform. To perform the wavelet transform does not require the explicit forms of $\phi(x)$ and $\psi(x)$ but only depends on $h(k)$ and $g(k)$. Consider a J-level wavelet decomposition which can be written as

$$f_0(x) = \sum_k c_{0,k}\phi_{0,k}(x)$$
$$= \sum_k \left(c_{J+1,k}\phi_{J+1,k}(x) + \sum_{j=0}^{J} d_{j+1,k}\psi_{j+1,k}(x)\right) \quad (6)$$

Where coefficients $c_{0,k}$ are given and coefficients $c_{j+1,n}$ and $d_{j+1,n}$ at scale $j+1$ are related to the coefficient $C_{j,k}$ at scale j through

$$c_{j+1,n} = \sum_k c_{j,k}h(k-2n)$$
$$d_{j+1,n} = \sum_k c_{j,k}g(k-2n) \quad (7)$$

Where $0 \le j \le J$. Thus, (7) provides a recursive algorithm for wavelet decomposition through $h(k)$ and $g(k)$, and the final outputs include a set of J-level wavelet coefficients $d_{j,n}$, $1 \le j \le J$, and the coefficient $c_{J,n}$ for a low-resolution component $\phi_{J,k}(x)$. Similarly, recursive algorithm can be derived for function synthesis based on its wavelet coefficients $d_{j,n}$, $1 \le j \le J$ and $c_{J,n}$

$$c_{j,k} = \sum_n c_{j+1,n}h(k-2n) + \sum_n d_{j+1,n}g(k-2n) \quad (8)$$

It is convenient to view the decomposition (7) as passing a signal $c_{j,k}$ through a pair of filters H and G with impulse responses $\hat{h}(n)$ and $\hat{g}(n)$ and down sampling the filtered signals by two(dropping every other sample), where $\hat{h}(n)$ and $\hat{g}(n)$ are defined as

$$\hat{h}(n) = h(-n),\ \hat{g}(n) = g(-n).$$

The pair of filters H and G correspond to the halfband lowpass and highpass filters, respectively, and are called the *quadrature mirror filters* in the signal processor literature. The reconstruction procedure is implemented by up sampling the sub signals c_{j+1} and d_{j+1} (inserting a zero between neighboring samples) and filtering with $h(n)$ and $g(n)$, respectively, and adding these two filtered signals together. Usually the signal decomposition scheme is performed recursively to the output of the lowpass filter $\hat{h}$. This leads to the conventional wavelet transform or the so-called pyramid-structured wavelet decomposition.

3.1 Texture feature extraction

Algorithm: Tree-Structured Wavelet Transform

1) A textured image is decomposed with 2-D two-scale wavelet transform into 4 sub images, which can be viewed as the parent and children nodes in a tree.

2) Energy of each decomposed image (children node) is calculated as follows. That is, if the decomposed image is $x(m,n)$, with $1 \le m \le M$ and $1 \le n \le N$, the energy is

$$e = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|x(m,n)|$$

3) If the energy of a sub image is significantly smaller than others, we stop the decomposition in this region since it contains less information. This step can be achieved by comparing the energy with the largest energy value in the same scale. That is, if $e < Ce_{max}$, stop decomposing this region where C is a constant less than 1.

4) If the energy of a sub image is significantly larger, the above decomposition procedure is applied to the sub image.

Practically, the size of the smallest sub images should be used as a stopping criterion for further decomposition. If the decomposed channel has a very narrow size, the location and energy value of the feature may vary widely from sample to sample so that the feature may not be robust. According to our experience, the size of the smallest sub images should not be less than 16x16. Consequently, if the input image size is 256x256 (or 64x64), a 4-level (or 2-level) tree-structured wavelet transform is appropriate. It is also worthwhile to point out that the above tree- structured wavelet transform provides a non-redundant representation, and it takes no more space to store the wavelet coefficients than it does to store the original image.

3.2 Selection of texture features

An appropriate way to perform the wavelet transform for textures is to detect the significant frequency channels and then to decompose them further.

It is observed that it is usually unnecessary and expensive to decompose all sub signals in each scale to achieve a full decomposition. The following criterion is used to avoid a full decomposition.

$$e(x) = \frac{1}{N}\|x\|l = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (9)$$

Where $x = (x_1,\ldots,x_N)$, as the energy function to locate dominant frequency channels. Although there exists other norms such as the l_2-norm for the energy function, we find that the l_1 and l_2 norms make little difference in the final results.

3.3 Method of texture discrimination

K- nearest neighbor is used as the classifier in the proposed approach. After selecting a feature subset, according to the successive scheme, *k*-nearest neighbor classifier scheme for a set of features is implemented. Each feature is normalized by its mean and variance, of a total of '*n*' samples one sample is held out to classify. Let '*Xt*' be the test sample and '*Xd*' be the design or training sample. The Euclidean distance between the test sample and the training sample in the normalized feature space is used to determine the *k*-nearest neighbors of '*Xt*'. The classifier then assigns '*Xt*' to the class most frequently encountered in the *k*-neighbors.

4 Theory of Gabor Filter

In the proposed work, the Gabor filters are generated by using three different radial center frequencies and eight orientations as described by Tou J.Y, Tay Y.H. and Lau P.Y. in 2007[19]. The convolution is first performed by applying Fast Fourier transform (FFT), point to point multiplication and Inverse Fast Fourier transform (IFFT). In order to minimize the dimensionality of the feature set Gabor filters are down sized and Singular Value Decomposition is used as described by Tou J.Y, Tay Y.H. and Lau P.Y. in 2007.

5. EXPERIMENTAL SET-UP

Figure.1 shows the experimental set-up. Specimens made of different manufacturing processes – Milling, Shaping, EDM and Sandblasting are used in the classification experiment. Table 1 and 2 shows sample details of Milled and Shaped components. The training set for each class comprised of 16 non-overlapping 32x32 sub images (Figure.2) taken from 512x480 digitized version of the above textures.

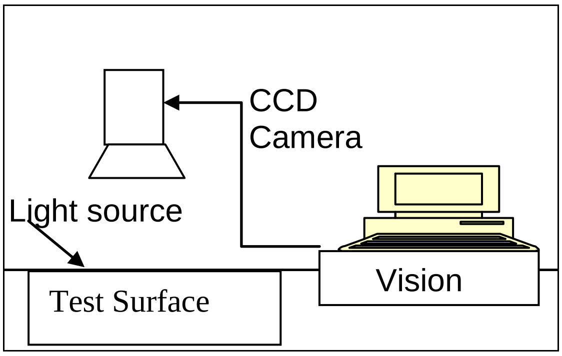

Fig.1:Experimental set-up used for classifying surface textures.

The vision system (Figure.1) consists of a CCD (Charge Coupled Device) Camera PULNIX for grabbing the image of a machined surface, illuminated by normal lighting. A higher end computer (server) used for storing and processing of surface image. The server also consists of a special purpose, advanced image processing hardware for quick processing of surface images. The images are processed for different types of noise including electronic noise by using special software designed and developed for this purpose. The software installed in the server is also used for extracting features for classification of different textures.

5.1 Specimen Preparation

Specimens are prepared by various machining operations such as Milling Shaping, EDM and Sandblasting processes to produce different machined surface textures, by varying machining parameters Table 1 and 2 shows sample details of Milled and Shaped components. Figure 2 shows the captured images are obtained from vision system using CCD (charge coupled device) Camera.

Table 1: Details of Milled components

Texture ID	Speed (rpm)	Depth of Cut (mm)	Feed (mm/ min)	Stylus Ra (µm) value
M1	280	0.4	12.5	1.31
M2	280	0.4	31.5	1.53
M3	280	0.4	80.0	3.18
M4	280	0.4	100.0	3.30
M5	280	0.4	200.0	2.80
M6	280	0.4	250.0	3.70

Texture ID	Speed (rpm)	Depth of Cut (mm)	Feed (mm/ stroke)	Stylus Ra(µm) value
S1	30	0.5	0.2	14
S2	30	0.5	0.4	41
S3	30	0.5	0.6	58
S4	30	0.5	0.8	60
S5	30	0.5	0.2	12

Table 2: Details of Shaped components

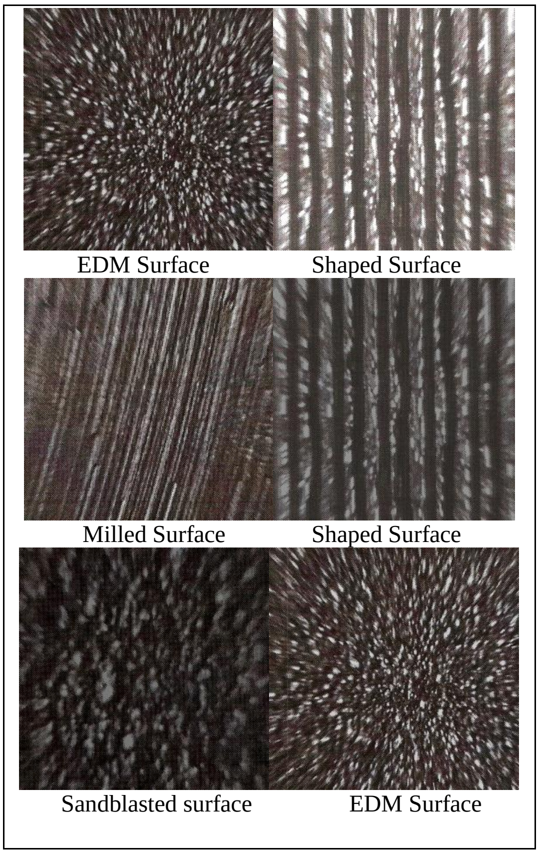

Fig.2 Sample images of training set.

Figure 3 and 4 shows sample images of test set.

6. *CLASSIFICATION USING TREE-STRUCTURED WAVELET TRANSFORM*

The following paragraphs highlight the significant steps in the classification algorithm.

6.1 **Learning phase**

1) Given *m* samples are obtained from the same texture, each sample image is decomposed with the tree-structured wavelet transform and the normalized energy is calculated at its leaves which defines an energy function on the spatial/frequency domain known as the *energy map*.
2) A representative *energy map* is generated for each texture by averaging the *energy maps* over all *m* samples.
3) The process is repeated for all textures.

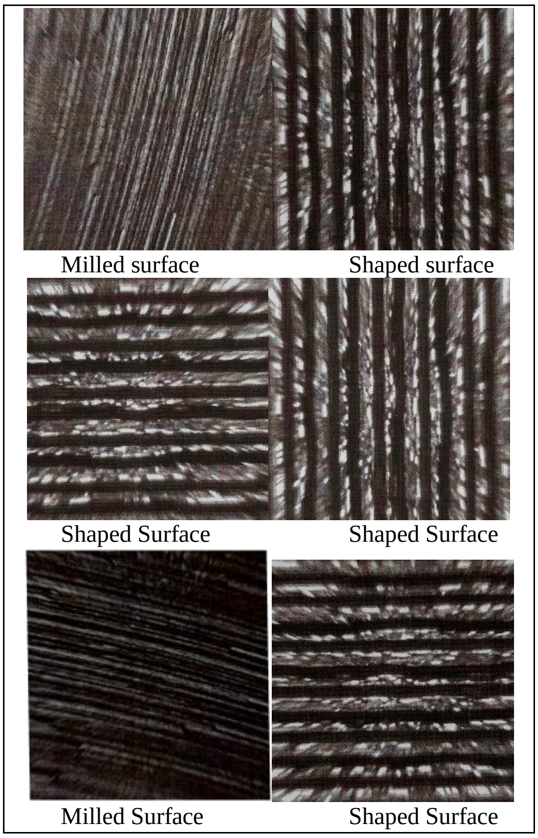

Fig.3 Sample images of test set.

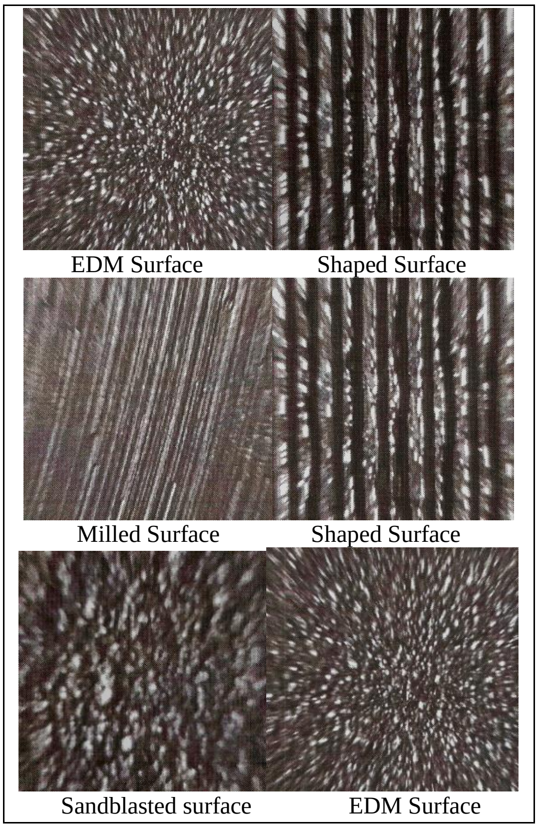

Fig.4 Sample images of test set.

6.2 **Classification phase**

1) An unknown texture is decomposed with the tree-structured wavelet transform and its *energy map* is determined.
2) The first J dominant channels are selected which are the leaf nodes in the *energy map* with the largest energy values as features. This feature set is denoted by $x = (x_1,\ldots,x_J)$.
3) For texture i in the database, pick up the energy values in the same channels are located and the energy value is denoted by by
$mi = (m_{i,1},\ldots\ldots m_{i,J})$.
4) The discrimination function for textures in the candidate list is calculated by

$$\boldsymbol{Di = \textbf{distance } (x, mi)} \tag{10}$$

5) Assign the unknown texture to texture i
If $Di < Dj$ for all $j \neq i$.

The above algorithm uses the energy values at the J most dominant channels as features for classification. Thus, it implicitly assumes that high energy means better discriminability.

Table 3: The classified results of training set

Real Samples of Class	1	2	3	4	C.R.R
1	50	0	0	0	100
2	3	47	0	0	94
3	0	3	47	0	94
4	0	0	0	50	100

Average C.R.R = 97%

<u>Conventions used in Table 3</u>:
Class 1: Shaped surface; 2: EDM surface; 3: Milled surface; 4: Sand blasted surface; C.R.R: Average Correct Recognition rate.

The entire set of training samples is classified in this way, holding out a new sample each time (Table 3). The classification accuracy is 97% in Tree-Structured Wavelet Transform.

7. *Classification using Gabor Filters*

Surface texture extraction experiment consists of the following steps:

1. Texture feature extraction
2. Selection of texture features
3. Method of texture discrimination
4. Classification and results

7.1 **Texture feature extraction:**

Different components, made from milling(Table1**)** ,shaping (Table2**)**, sandblasting and EDM, are selected for surface texture measurement. Gabor filters are generated by using different three radial centre and eight orientations. The convolution is performed by applying Fast Fourier Transform (FFT), point-to-point multiplication and inverse Fast Fourier Transform (IFFT).

7.2 **Selection of Texture features:**

Due to the complexity of the features produced, Gabor filters are down sampled and the singular value decomposition is used to reduce the dimensionality of the feature set.

7.3 **Method of texture discrimination:**

k-nearest neighbour is used as the classifier in the proposed approach. After selecting a feature subset, according to the successive scheme, k-nearest neighbour classifier scheme for a set of features is implemented. Each feature is normalized by its mean and variance. Of a total of 'n' samples one sample is held out to classify. Let 'Xt' be the test sample and 'Xd' be the design or training sample. The Euclidean distance between the test sample and the training sample in the normalized feature space is used to determine the k nearest neighbours of 'Xt'. The classifier then assigns 'Xt' to the class most frequently encountered in the k-neighbours.

Table 4 The classified results of training set

Real Sampl es of Class	1	2	3	4	C.R.R
1	50	0	0	0	100
2	3	47	0	0	93.75
3	0	3	47	0	93.75
4	0	0	0	50	100

Average C.R.R = 96%

Conventions used in Table 4:
Class 1: Shaped surface; 2: EDM surface; 3: Milled surface; 4: Sand blasted surface; C.R.R: Average Correct Recognition rate.

The entire set of training samples is classified in this way, holding out a new sample each time. The classification accuracy is 96%.

8. CONCLUSIONS

An attempt has been made in this paper to evaluate the effectiveness of (1) Gabor Filters and (2) Tree-Structured Wavelet Transform algorithms, in classifying different surface textures. The method is non-contact and non destructive in nature.

Texture classification by Gabor filter method has achieved the classification accuracy of 96% and the method could be used for classifying machined surfaces made out of EDM, Milling, Shaping, Grinding and Sandblasting.

Texture classification by Tree-Structured Wavelet Transform method has achieved the classification accuracy of 97% and the method could be used for classifying machined surfaces made out of EDM, Milling, Shaping, Grinding and Sandblasting.

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