World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:1, No:5, 2007

Feature Extraction for Surface Classification – An approach with Wavelets

Smriti H. Bhandari, and S. M. Deshpande

***Abstract*—**Surface metrology with image processing is a challenging task having wide applications in industry. Surface roughness can be evaluated using texture classification approach. Important aspect here is appropriate selection of features that characterize the surface. We propose an effective combination of features for multi-scale and multi-directional analysis of engineering surfaces. The features include standard deviation, kurtosis and the Canny edge detector. We apply the method by analyzing the surfaces with discrete wavelet transform (DWT) and dual-tree complex wavelet transform (DT-CWT). We used Canberra distance metric for similarity comparison between the surface classes. Our database includes the surface textures manufactured by three machining processes namely Milling, Casting and Shaping. The comparative study shows that DT-CWT outperforms DWT giving correct classification performance of 91.27% with Canberra distance metric.

***Keywords*—**Dual-tree complex wavelet transform, surface metrology, surface roughness, texture classification.

I. Introduction

THE need for quality control and performance testing has become an integral part of the production procedure. Surface finish plays an important role in several engineering applications. The study of surface texture is commonly referred to as Surface Metrology. It involves the measurement and characterization of surfaces and their relationship to the manufacturing process that generated the part and functional performance measures of the component.

A typical engineering surface consists of a range of spatial wavelengths with different amplitudes. The high frequency or short wavelength components are referred to as roughness, the medium frequencies as waviness and low frequency components as form [1]. Different aspects of the manufacturing process generate different wavelength regimes and these affect the function of the manufactured part differently. By separating surface profile into various bands, it is possible to map the frequency spectrum of each band to the manufacturing process that generated it or to the functional aspects of the part. Thus filtering of surface profiles serves as a useful tool for process control and functional correlation. As current manufacturing trends are towards higher performance and tighter tolerances, there is a need for close monitoring of the process. Thus filtering of profiles to obtain finer bandwidths that better reflect the variations in the process or the intended function of the component is required. Use of wavelets for texture analysis is advantageous but real discrete wavelet transform (DWT) has two discouraging aspects: lack of shift invariance and poor directional selectivity. It is found that both the problems can be solved effectively by the complex wavelet transform (CWT) by introducing limited redundancy into the transform. In CWT, filters have complex coefficients and generate complex output samples. However, a further problem arises here because perfect reconstruction becomes difficult to achieve for complex wavelet decomposition beyond level 1, when the input to each level becomes complex. To overcome this problem, Kingsbury [2], [3] has proposed dual-tree complex wavelet transform (DT-CWT) which allows perfect reconstruction while still providing the other advantages of complex wavelets. Further after studying the metrological characteristics [4], it has been stated that DT-CWT filter is very suitable for the separation and extraction of the frequency components such has surface roughness, waviness and form. In many attempts to characterize and categorize surfaces with wavelet transform the features like energy, standard deviation, weighted standard deviation were used. The goal of feature extraction is to improve the effectiveness and efficiency of analysis and classification.

In this paper, we propose a combination of three texture descriptors namely Standard Deviation, Kurtosis and Canny edge detector. DWT and DT-CWT are used as the tools for analysis. Euclidean and Canberra distance metrics are used for similarity estimation.

II. The Dual-Tree Complex Wavelet Transform

In DT-CWT, to achieve perfect reconstruction and good frequency characteristics, two parallel fully decimated trees with real filter coefficients are used [2]. The 1-D DT-CWT decomposes a signal $f(x)$ in terms of a complex shifted and dilated mother wavelet $\psi(x)$ and scaling function $\phi(x)$.

$$f(x) = \sum_{l \in Z} s_{j_0,l}\phi_{j_0,l}(x) + \sum_{j \geq j_0}\sum_{l \in Z} c_{j,l}\psi_{j,l}(x) \qquad (1)$$

Manuscript received June 15, 2007. This work was supported by Department of Science and Technology, New Delhi (India) under research fellowship (SR/WOS-A/ET-50/2004).

Smriti H. Bhandari is with Department of Computer Science and Engineering, Walchand College of Engineering, Sangli, India working as a research fellow (corresponding author phone: +91 9422407841; fax: +91 233 2300831; e-mail: b_smriti@rediffmail.com).

Dr. S. M. Deshpande is professor in the Department of Computer Science and Engineering, Walchand College of Engineering, Sangli, India (e-mail: s_m_deshpande@yahoo.com).

where $s_{j_0,l}$ is scaling coefficient and $c_{j,l}$ is complex wavelet coefficient with ϕ_{j_0} and $\psi_{j,l}$ complex: $\phi_{j_0} = \phi^r_{j_0,l} + \sqrt{-1}\phi^i_{j_0,l}$, $\psi_{j_0} = \psi^r_{j_0,l} + \sqrt{-1}\psi^i_{j_0,l}$. The $\psi^r_{j,l}\psi^i_{j,l}$ are themselves real wavelets: the complex wavelet transform is a combination of two real wavelet transforms, in 1-D the $\left\{\phi^r_{j_0,l}, \phi^i_{j_0,l}, \psi^r_{j_0,l}, \psi^i_{j_0,l}\right\}$ form a tight wavelet frame with two times redundancy. The real and imaginary parts of the DT-CWT are computed using separate filter bank structures with wavelet filters h_0 and h_1 for the real part and g_0, g_1 for the imaginary part.

The DT-CWT is implemented using separable transforms and by combining subband signals appropriately. Specifically, the 1-D DT-CWT is implemented using two filter banks in parallel operating on the same data as illustrated in Fig. 1. Thus far, the dual tree does not appear to be a complex transform at all. However, when the outputs from the two trees in Fig. 1 are interpreted as the real and imaginary parts of complex coefficients, the transform effectively becomes complex.

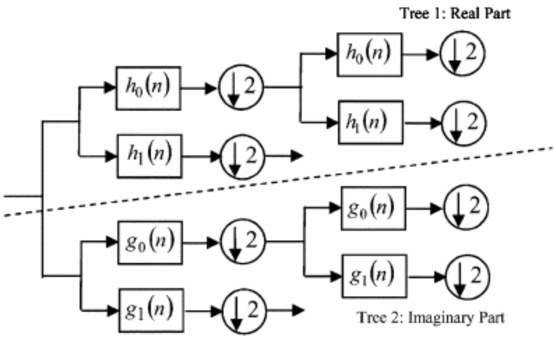

Fig. 1 The 1-D dual-tree complex wavelet transform

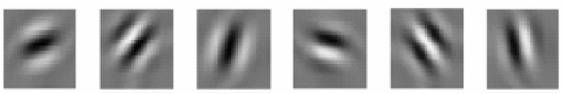

Fig. 2 Impulse response of six wavelet filters of complex transform

In 2-D, the CWT decomposes an image $f(x,y)$ using dilation and translations of a complex scaling function and six complex wavelet functions

$$f(x,y) = \sum_{k\in Z^2} s_{j_0,k}\phi_{j_0,k}(x,y) + \sum_{b\in\theta}\sum_{j\geq j_0}\sum_{k\in Z^2} c^{\theta}_{j,k}\psi^{\theta}_{j,k}(x,y) \qquad (2)$$

Impulse response of these six wavelets associated with 2-D complex wavelet transform is illustrated in Fig. 2 as a gray-scale image. These six wavelet subbands of the 2-D DT-CWT are strongly oriented in $\theta = \{+15^\circ, +45^\circ, +75^\circ, -15^\circ, -45^\circ, -75^\circ\}$ direction and captures image information in that direction.

Frequency-domain partition of complex wavelet transform resulting from two levels decomposition is shown in Fig. 3. The complex wavelet transform, shown in Fig. 3, can discriminate between features at positive and negative frequencies. Hence, there are six subbands capturing features along lines at angles of $\{+15^\circ, +45^\circ, +75^\circ, -15^\circ, -45^\circ, -75^\circ\}$.

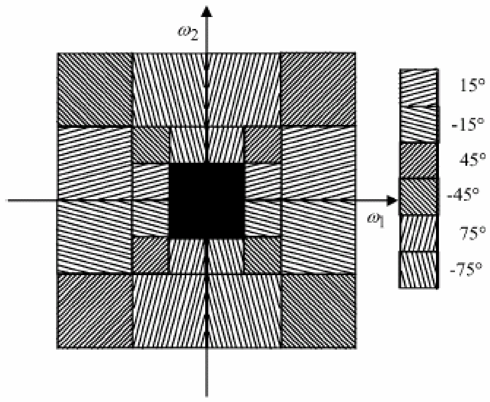

Fig. 3 Frequency domain partition in complex wavelet transform resulting from two level decomposition

III. The Proposed System

The proposed system has four major stages.

A. Image Acquisition

The first stage of the system is that of image acquisition. We used Nikon D70S digital camera with 105 mm F 2.8 macro lens to acquire images of engineered surfaces. Fig. 4 shows the experimental set-up with camera and the light source system to acquire the digital images on the interfaced computer system.

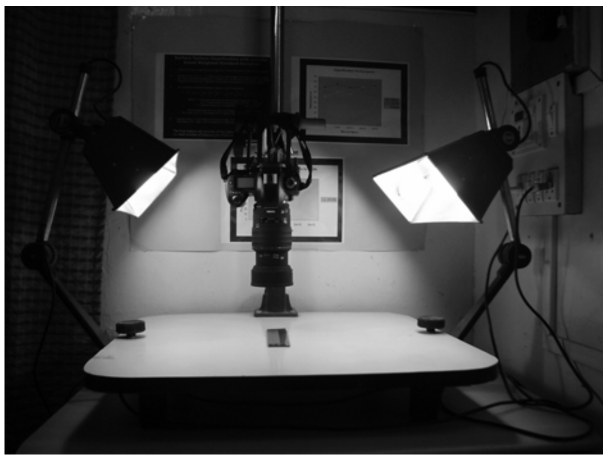

Fig. 4 Experimental set-up for Image Acquision

B. Feature Extraction

Feature extraction is concerned with the quantification of texture characteristics in terms of a collection of descriptors or quantitative feature measurements, often referred to as a feature vector. The choice of appropriate descriptive parameters will radically influence the reliability and effectiveness of subsequent feature qualification through classification.

Algorithm for texture analysis and feature extraction with DT-CWT:

1) Subject the gray scale texture image to an L-level dual-tree complex wavelet transform decomposition. We use the Near-symmetric 13,19 tap filters as the level 1 filter and Q-shift 14,14 tap filters for other level filtering, which are described in Kingsbury's paper [3].
2) At each level (i=1, 2, …L), there are six sub-images at orientations $+15^\circ, +45^\circ, +75^\circ, -15^\circ, -45^\circ, -75^\circ$ for real part of complex wavelet as well as six sub-images at similar orientations for complex part of the wavelet. For each sub-image, compute the following three features.
   i. Edge descriptor
      Using Canny edge detection method [5], find out the edges in the sub-image. If edge is found represent the pixel as 1 and compute total number of such pixels containing edges in the image.
   ii. Standard deviation
      The standard deviation of the image gives a measure of the amount of detail in that subband.
   iii. Kurtosis
      It measures the peakedness or flatness of the distribution and is given by

$$k = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4 \tag{3}$$

      where μ is the sample mean of the N pixels within the image and σ is standard deviation
3) Compute the three features for original image also.
   Thus the length of the feature vector is 3 features * [(L * 12 subimages at each level) + original image].

C. Training

We use supervised classification method. So we need to define the texture classes first. We used three texture databases namely Milling, Casting and Shaping. Milling database has six classes, Casting has nine classes and Shaping has eight classes. In the training phase, for each texture class twenty samples are selected randomly and using proposed algorithm feature set is formed. Average of these features for each texture class is stored in the respective texture feature database. This feature database is used for texture classification.

D. Texture Classification

In the texture classification phase, the texture feature set, for the test sample X is computed using the proposed algorithm. The feature database of texture classes *k* prepared during training phase is used to compare the features of test image.

The distance metric can be termed as similarity measure. The distance between the texture classes stored in the database and the test image is computed and used for classification. The test image is more similar to the database class if the distance is smaller. If *N* is the number of features in feature set *f*, $f_j(x)$ is the j^{th} texture feature of the test sample X and $f_j(k)$ is the j^{th} texture feature of k^{th} texture class in the database, then the Euclidean and Canberra distance metrics are described as below:

Euclidean or Minkowsky L2 metric

$$d_E(k) = \sqrt{\sum_{j=1}^{N}\left[f_j(x) - f_j(k)\right]^2} \tag{4}$$

Canberra

$$d_{Can}(k) = \sum_{j=1}^{N}\frac{\left|f_j(k) - f_j(x)\right|}{\left|f_j(k)\right| + \left|f_j(x)\right|} \tag{5}$$

In Canberra distance metric, the individual feature components are normalized before finding the distance between the two images.

IV. Experimental Results

We have carried out the experiments on three texture databases. The databases are prepared by taking images of the standard (master) roughness comparison specimen manufactured by three machining processes namely Milling, Casting and Shaping. (Only flat i.e. non-curved surfaces are used.) We used the image acquisition system as shown in Fig. 4 to take the images. Milling database has six classes, Casting database has nine classes whereas Shaping database has eight classes. One image from each class in the database can be seen in Fig. 5~7. Label associated with an image indicates surface roughness value.

For each class we are having thirty gray scale images. Thus for milling 180 images, Casting 270 images and Shaping 240 images of size 256 X 256 pixel are used. Twenty from each class are used for training purpose whereas 690 images are tested for classification. Correct classification of an image ultimately describes the surface roughness value.

We implemented the approach with DWT and DT-CWT as analysis tools. The classification performance is the rate of correct classification of surface textures. Euclidean and Canberra distance measures are used. The comparative chart is shown in Fig. 8. It is found that Canberra distance outperforms Euclidean distance.

A. Implementation with DT-CWT

As per the proposed algorithm a 4-level decomposition scheme is used. Thus for each class feature set includes 3*[(4*12)+1]=147 features. We have tested all the combinations of three texture descriptors and compared the performances. The classification results using Canberra distance metric with various combinations of texture descriptors are summarized in Table I.

It is found that the feature set comprising 147 features having the Canny edge descriptor, standard deviation and kurtosis features is robust and gives the best performance of 95.56%, 84.07% and 94.17% on Milling, Casting and Shaping databases respectively resulting in the overall performance of correct classification as 91.27%.

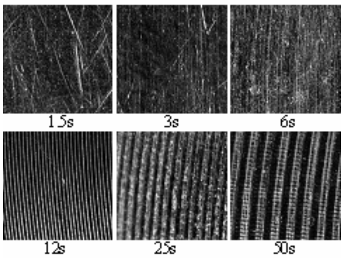

Fig. 5 Milling Database

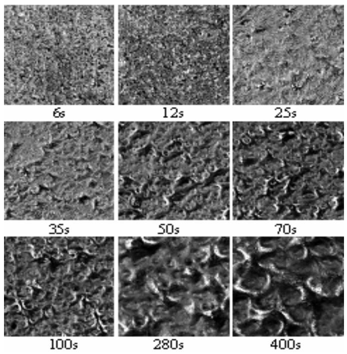

Fig. 6 Casting Database

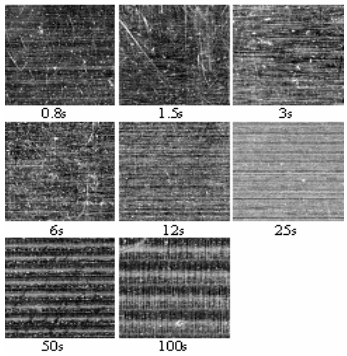

Fig. 7 Shaping Database

TABLE I
CLASSIFICATION PERFORMANCE - DT-CWT WITH DIFFERENT TEXTURE DESCRIPTORS

TD / Class	Texture Descriptor [Number of Features]						
	CED [49]	*SD [49]*	*Kurtosis [49]*	*CED + SD [98]*	*CED + Kurtosis [98]*	*SD + Kurtosis [98]*	*CED + SD + Kurtosis [147]*
Mill 1.5s	80.00	70.00	63.33	83.33	73.33	80.00	86.67
Mill 3s	90.00	76.67	83.33	86.67	86.67	90.00	96.67
Mill 6s	100.00	83.33	100.00	93.33	100.00	96.67	100.00
Mill 12s	96.67	100.00	63.33	100.00	83.33	96.67	96.67
Mill 25s	96.67	90.00	96.67	100.00	100.00	100.00	100.00
Mill 50s	80.00	93.33	60.00	96.67	83.33	90.00	93.33
Milling DB	**90.56**	**85.56**	**77.78**	**93.33**	**87.78**	**92.22**	**95.56**
Cast 6s	73.33	63.33	80.00	66.67	90.00	66.67	66.67
Cast 12s	76.67	93.33	100.00	93.33	100.00	100.00	100.00
Cast 25s	70.00	76.67	90.00	80.00	96.67	80.00	83.33
Cast 35s	66.67	50.00	73.33	66.67	83.33	70.00	73.33
Cast 50s	83.33	76.67	80.00	80.00	83.33	86.67	90.00
Cast 70s	60.00	83.33	70.00	86.67	73.33	86.67	86.67
Cast 100s	66.67	56.67	66.67	63.33	66.67	83.33	83.33
Cast 280s	80.00	76.67	63.33	80.00	70.00	83.33	83.33
Cast 400s	76.67	80.00	76.67	96.67	80.00	90.00	90.00
Casting DB	**72.59**	**72.96**	**77.78**	**79.26**	**82.59**	**82.96**	**84.07**
Shape 0.8s	70.00	80.00	80.00	80.00	86.67	80.00	83.33
Shape 1.5s	53.33	83.33	86.67	90.00	93.33	90.00	90.00
Shape 3s	56.67	73.33	86.67	76.67	93.33	80.00	80.00
Shape 6s	70.00	100.00	46.67	93.33	53.33	100.00	100.00
Shape 12s	66.67	100.00	80.00	100.00	83.33	100.00	100.00
Shape 25s	80.00	100.00	100.00	100.00	100.00	100.00	100.00
Shape 50s	90.00	100.00	100.00	100.00	100.00	100.00	100.00
Shape 100s	86.67	100.00	100.00	100.00	100.00	100.00	100.00
Shaping DB	**71.67**	**92.08**	**85.00**	**92.50**	**88.75**	**93.75**	**94.17**
OVERALL PERFORMANCE	**78.27**	**83.53**	**80.19**	**88.36**	**86.37**	**89.65**	**91.27**

CED = Canny Edge Detector, SD = Standard Deviation

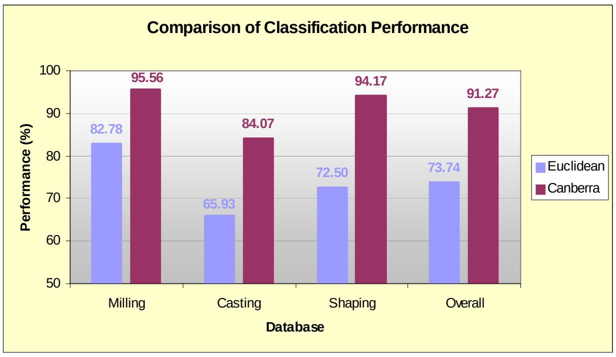

Fig. 8 Performance Comparison Euclidean Vs Canberra distance metric with DT-CWT

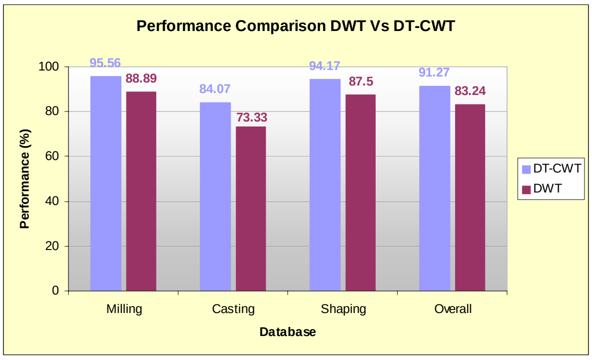

Fig. 9 Performance Comparison DWT Vs DT-CWT with Canberra distance metric

B. *Implementation with DWT*

We carried out similar experiments with DWT [6] as an analysis tool and the same texture descriptors. We carried out 4-level DWT decomposition of original image and four counter parts of it namely the images rotated by 90^0, 180^0, 270^0 and the complemented image. In our previous experiments [7] it has been found that Battle-Lemarie wavelet bases are good for surface metrology applications; so we use the same as the mother wavelet. We computed the proposed features from each sub-image. Also we computed SD, kurtosis and edge descriptor of original image. Thus the length of the feature vector is 5 images * [3 texture descriptors * (4 Levels * 3 subimages + 1)] + 3 features of original image that is total 198 features. We achieved the correct classification performance of 83.24% with Canberra distance metric over all three databases. The comparative results are depicted in Fig. 9.

V. Conclusion

It is found that in this application of surface metrology DT-CWT out performs DWT showing the improvement in the correct rate of classification. DT-CWT extracts information in six directions where as DWT extracts information in horizontal, vertical and diagonal orientations. The DWT performance with only original image having 42 features was 73.22%. We tried to improve the DWT approach by using rotated and complemented images and achieved the performance of 83.24%.

In case of DT-CWT, when CED, SD and Kurtosis are used separately as texture descriptors we got the performances as 78.27%, 83.53% and 80.19% respectively. Our experiments suggest that the combination of these three descriptors is useful to categorize surfaces with their roughness values with the performance of 91.27%.

Canny edge detector is an effective texture descriptor in our application. In a specific texture database all the textures are manufactured by the same machining process with differed dimension of machine tool used. Thus the number of primitives or texture elements in a specified area of the texture differs according to the texture class. Hence the number of pixels containing edges varies according to the texture pattern. Thus it proves to be a very good texture descriptor in this application.

This method of feature extraction and surface texture classification will be useful for surface roughness evaluation in on line product quality monitoring.

It is important to note that the rate of correct classification differs with respect to the database; that is the machining process used to manufacture the surface. This algorithm is tested with only three databases namely milling, casting and shaping. These images are the surface textures manufactured by respective machining processes. The work can be further extended to test the performance for the textures manufactured by other machining processes namely grinding, gritblasting, hand filing, linishing, shot blasting etc. Our future study will also undertake the work regarding computation of efficiency of these approaches.

Acknowledgment

The authors wish to thank Dr. P. J. Kulkarni and Dr. M. Y. Khire for their suggestions and support during this work.

References

[1] ASME B46.1, Surface texture (Surface roughness, waviness and lay), 1995.
[2] N. G. Kingsbury, "Image processing with complex wavelets," *Phil. Trans. Roy. Soc. London A*, vol. 357, pp.2543-2560, September 1999.
[3] N. G. Kingsbury, "Complex wavelets for shift invariant analysis and filtering of signals," Journal of applied and computational harmonic analysis, Vol. 10, No.3, pp.234-253, May 2001.
[4] W. Zeng, X. Jiang, and P. Scott, "Metrological characteristics of dual-tree complex wavelet transform for surface analysis," *Meas. Sci. Technol*., 16, pp. 1410-1417, 2005.
[5] J. Canny, "A computational approach to edge detection," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, PAMI-8, no. 6, pp. 679-698, 1986.
[6] R. C. Gonzalez, R. E. Woods, and S. L. Eddins, *Digital Image Processing Using Matlab*, 1st Indian Reprint, Pearson Education, 2004, ch. 7.
[7] S. H. Bhandari and S. M. Deshpande, "Wavelets for surface Metrology," Accepted for presentation in international conference ACVIT, Nov. 2007.