Wavelets for Surface Metrology

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Abstract

Surface Metrology deals with study of surface textures. This work is an attempt to use wavelets as a tool for analyzing surface textures of engineered surfaces. We focused on roughness evaluation of surfaces. We used various wavelet bases for analyzing and extracting features from texture images. Experimentation is carried out using standard deviation (SD), weighted standard deviation (WSD), energy, entropy, kurtosis and their combinations as texture descriptors. The feature combination of WSD, entropy and kurtosis gives good results over all other texture descriptors. We also compared various distance metrics used as similarity measures while classifying the textures into the appropriate roughness classes. Experiments are carried out with five wavelet bases and nine distance metrics. The comparative results are presented. It is found that Battle-Lemarie wavelets perform well with proposed feature set and cosine distance metric. Three surface texture databases namely Milling, Casting and Shaping are used for experimentation. The overall classification performance is 79%.

Keywords: Surface texture classification, wavelet transform, surface metrology, distance metrics.

I. Introduction

Surface finish plays an important role in several engineering applications. The study of surface texture is commonly referred to as Surface Metrology [1]. 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 [2]. 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. A linear space-scale representation called wavelet transform can be used as a tool for the multi-scale analysis of engineering surfaces. Its non-stationary and multi-scale view of a signal offers the potential for characterizing multi-scale features of surfaces. An attempt to link the multi-scale features of an engineering surface with both its manufacturing and functional aspects was made [3] using wavelet transform. Extension of the multi-scale concepts to the three-dimensional surface analysis can be found in [4], where the capability of two-dimensional wavelet representation for differentiating several spatial orientations was utilized for pattern analysis. Use of wavelets for surface texture analysis is advantageous but having the lack of directional selectivity. Extensive study was carried out to investigate transmission characteristics of different wavelet bases and it has been reported that bior6.8 and coif4 are good choices [5] for surface analysis. In this paper, we propose an approach of surface texture analysis that uses features from original as well as rotated counterparts of image. Thus there is significant improvement in the classification results. We investigated the proposed approach using five wavelet bases namely db6, coif4, bior6.8, blm16 and blm18 and various texture descriptors. Classification is carried out with nine distance metrics namely Euclidean, Manhattan, Canberra, Chebychev, Squared chi-square, Squared Chord, Bray-Curtis and Cosine angle. The comparison of performances is presented. We found that Battle-Lemarie wavelets give classification performance of 79% with the cosine angle metric. Thus the classification performance depends on the choice of wavelet, selection of texture descriptors or the features and the distance metric used for similarity estimation.

This paper is organized as follows: in Section II, wavelet transform is described in brief. In Section III, the proposed system and the algorithm is presented for surface texture analysis and feature computation. Section IV is devoted to implementation and experimental results and the conclusion is provided in Section V.

II. The Wavelet Transform

The wavelet is an attractive tool in surface texture analysis because it can decompose a surface into multiscale representation in a very efficient way.

The wavelet transform (WT) is a mapping of the signal to the time-scale joint representation. By WT, we mean 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 $\psi(x)$ known as mother wavelet. i.e.

$$\psi_{m,n}(x) = 2^{-m/2}\psi(2^{-m}x - n) \qquad (1)$$

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

$$c_{m,n} = \int_{-\infty}^{+\infty} f(x)\psi_{m,n}(x)dx \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (2)$$

and the synthesis formula

$$f(x) = \sum_{m,n} c_{m,n}\psi_{m,n}(x) \qquad (3)$$

can be used to recover $f(x)$ from its wavelet coefficient.

To construct the mother wavelet $\psi(x)$, we may first determine a scaling function $\phi(x)$ which satisfies

$$\phi(x) = \sqrt{2}\sum_{k} h(k)\phi(2x-k) \qquad (4)$$

Then, the mother wavelet $\psi(x)$ is related to the scaling function via

$$\psi(x) = \sqrt{2}\sum_{k} g(k)\phi(2x-k) \qquad (5)$$

Where $g(k) = (-1)^k h(1-k)$ (6)

The coefficients $h(k)$ in (4) have to meet several conditions for the set of basis wavelet functions in (1) to be unique, orthonormal and have a certain degree of regularity. In practice, the transform is computed by applying a separable filter bank to the image:

$$\begin{aligned} A &= [L_x * [L_y * I]_{\downarrow 2,1}]_{\downarrow 1,2} \\ H &= [L_x * [G_y * I]_{\downarrow 2,1}]_{\downarrow 1,2} \\ V &= [G_x * [L_y * I]_{\downarrow 2,1}]_{\downarrow 1,2} \\ D &= [G_x * [G_y * I]_{\downarrow 2,1}]_{\downarrow 1,2} \end{aligned} \qquad (7)$$

Where * denotes the convolution operator, ↓2, 1(↓1, 2) denotes the down sampling along the Rows (columns) and I is the original image, L and G is low pass and high pass filters, respectively. A is obtained by low pass filtering and is referred to as the low resolution image at scale one H, V, D are obtained by band pass filtering in a specific direction and thus contain directional detail information at scale one. The original image I is thus represented by a set of sub images at several scales. Every detail sub image contains information of a specific scale and orientation. Spatial information is retained within the sub image. Wavelets are functions generated from one single function by dilations and translations. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different levels, where each level is further decomposed with a resolution adapted to that level. Figure 1 shows the three-level wavelet decomposition.

The sub-bands labeled H, V and D correspond to Horizontal, Vertical and Diagonal coefficients respectively, representing the detail images, while the sub-band A corresponds to coefficients representing the approximation image.

The values of transformed coefficients in approximation and detail images are essential features, which are useful for texture classification and segmentation. In other words, the features derived from these approximation and detail coefficients uniquely characterize a texture.

III. The Proposed System

The overall system is divided into following sub systems.

A) Texture Analysis and Feature Extraction for database images - Training.

B) Texture Analysis and Feature Extraction for test images.

C) Texture Classification using similarity measurement between feature sets of texture database classes and test image.

The block diagram of the proposed system is presented in Figure 2.

Algorithm for texture analysis and feature extraction

1) Subject the gray scale texture image to a L-level discrete wavelet decomposition.
2) At each level (i=1, 2 … L), there are four sub-images. One approximation image and three detailed components / images (LH, HL and HH or Horizontal, Vertical and Diagonal components). Compute the features (SD, WSD, Energy, Entropy and Kurtosis) from all these images.
3) The weighted standard deviation [6] feature vector is as below:

$$f = \begin{Bmatrix} \sigma_1^H, \sigma_1^V, \sigma_1^D, \frac{1}{2}\sigma_2^H, \frac{1}{2}\sigma_2^V, \frac{1}{2}\sigma_2^D, \ldots, \\ \frac{1}{2^{L-1}}\sigma_L^H, \frac{1}{2^{L-1}}\sigma_L^V, \frac{1}{2^{L-1}}\sigma_L^D, \frac{1}{2^{L-1}}\sigma_L^A \end{Bmatrix} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

where σ_i^M = Standard deviation of the M detail image at i^{th} level

M = H (Horizontal)/ V(Vertical)/ D(Diagonal) component

σ_i^A = Standard deviation of approximation image at i^{th} level

The standard deviation of each sub image at level i is weighted by the factor $(1/2^{i-1})$. The length of the feature vector is $3L+1$.

Kurtosis measures the peakedness or flatness of the distribution and is given by

$$k = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Where μthe sample is mean of the N pixels within the image and σ is standard deviation

4) Repeat steps 1-3 five times for original image, complementary image and images at orientation 90º, 180º, and 270 º (achieved by rotating original image).

The final feature set consists of five feature vectors of length Number of texture descriptors * (3L+1) i.e. total number of features are Number of texture descriptors * [5*(3L+1)].

The standard deviations of the images give a measure of the amount of detail in that sub band. Since texture mainly consists of quasi-periodic spatial variations, we expect the higher frequency sub bands (lower levels of decomposition) to contain more texture information, so higher weights are given to these sub bands while computing WSD.

Training

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 texture analysis 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. For each texture family we have associated feature databases comprising features as SD, WSD, energy, entropy and kurtosis.

Classification

In the texture classification phase, the texture feature set, for the test sample X is formed using the proposed texture analysis algorithm. These features are compared with the feature values stored during training phase in the respective database of texture family with *k* classes. The distance metric can be termed as similarity measure. The similarity between two vectors is often determined by computing the distance between them using a certain distance metric. 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, fi (x)* is the jth texture feature of the test sample X and *fi(k)* is the j^{th} texture feature of k^{th} texture class in the database, then the nine distance metrics used are described as below [7][8]:

Euclidean or Minkowsky L2 metric

$$d_E(k) = \sqrt{\sum_{j=1}^{N} \left[f_j(x) - f_j(k) \right]^2} \quad \text{..(10)}$$

Manhattan or Minkowsky L1 metric

$$d_M(k) = \sum_{j=1}^{N} \left| f_j(x) - f_j(k) \right| \quad \text{(11)}$$

Canberra

$$d_{Can}(k) = \sum_{j=1}^{N} \frac{\left| f_j(k) - f_j(x) \right|}{\left| f_j(k) \right| + \left| f_j(x) \right|} \quad \text{(12)}$$

Chebychev

$$d_C(k) = \max_{j=1}^{N} \left| f_j(x) - f_j(k) \right| \quad \text{(13)}$$

Chi-square

$$d_{Chi}(k) = \sum_{j=1}^{N} \frac{1}{sum_j} \left(\frac{f_j(k)}{size_k} - \frac{f_j(x)}{size_x} \right)^2 \quad \text{(14)}$$

Where sum_j is the sum of all values for attribute *j* occurring in the training set, $size_x$ is the sum of all values in the vector $f_j(x)$ and $size_k$ is the sum of all values in the vector $f_j(k)$.

Squared Chi-square

$$d_{SChi}(k) = \sum_{j=1}^{N} \frac{\left(f_j(k) - f_j(x)\right)^2}{\left(f_j(k) + f_j(x)\right)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(15)$$

Squared Chord

$$d_{SC}(k) = \sum_{j=1}^{N} \left(\sqrt{f_j(k)} - \sqrt{f_j(x)}\right)^2 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(16)$$

Bray-Curtis

$$d_{BC}(k) = \sum_{j=1}^{N} \frac{\left|f_j(k) - f_j(x)\right|}{f_j(k) + f_j(x)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(17)$$

Cosine angle

$$d_{Cos}(k) = \cos^{-1} \frac{\sum_{j=1}^{N} f_j(k) f_j(x)}{\sqrt{\sum_{j=1}^{N}\left(f_j(k)\right)^2 \sum_{j=1}^{N}\left(f_j(x)\right)^2}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(18)$$

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 specimens manufactured by three machining processes namely Milling, Casting and Shaping. (only flat i.e. non-curved surfaces are used.) We used Nikon D70S digital camera with 105 mm F 2.8 macro lens. Figure 3 shows the experimental set-up with camera and the light source system to acquire the digital images on the interfaced computer system. 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 Figure 4. 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. For classification thirty images are tested. Correct classification of an image ultimately describes the surface roughness value.

Experiments are carried out using five wavelet bases namely db6, coif4, bior6.8, blm16 and blm18. (db - Daubechies wavelet, coif – Coiflet, bior6.8 – Biorthogonal 6.8, blm16- Battle Lemarie 16 tap, blm18 - Battle Lemarie 18 tap). A 3-level decomposition scheme is used. According to the step number 4 in our algorithm the features are extracted from original image and the four other counter parts of the same image. Thus for each class

feature set includes multiples of 5*[(3*3+1)] i.e. multiples of 50 features depending on the number of texture descriptors selected for analysis. We tested the algorithm with various texture descriptors namely SD, WSD, energy, entropy, kurtosis and their combinations. The results are as shown in Table 1.

To demonstrate effectiveness of our algorithm with rotated images, we have carried out the experiments with only the original image that is the feature vector comprising of multiples of 10 features. The classification results are shown graphically in Figure 5-7. The classification performance is the rate of correct classification of surface textures.

V. Conclusions

A simple approach to texture classification specifically for engineered surface textures is proposed that can be used as surface roughness evaluation technique for industrial applications. The classification performance is demonstrated experimentally that shows reasonably good results. Table 1 clearly describes that the combination of WSD, entropy and kurtosis is a better choice as texture descriptor than other individual or combinations of texture descriptors. Classification results as in Figure 5 show that cosine distance metric is good choice with Battle-Lemarie wavelet base. Further rate of correct classification differs with respect to the database. The shaping database shows the highest performance among the three whereas the Casting database shows the lowest performance. Figure 6 shows that Battle-Lemarie wavelet outperforms other wavelet bases. The performance over three databases is 79% with cosine distance metric. The results of the similar approach but only using original image (30 features only) are comparatively poor and the comparison is shown in Figure 7. By using rotated counter parts of the image we can able to obtain few directional details of the texture image. Further, in the proposed approach, though the number of features need to be compared are large, the performance is improved significantly than the approach with only 30 number of features.

There is a scope to study other variants of wavelet transform for surface metrology application and also to test few other distance metrics like Value Difference Metric (VDM), Heterogeneous Value Difference Function (HVDM), Interpolated Value Difference Metric (IVDM) and Windowed Value Difference Metric (WVDM) [7] etc. for specific application of texture analysis and classification. 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 check the performance for the textures manufactured by other machining processes namely grinding, grit blasting, hand filing, finishing, shot blasting etc. The transmission characteristics of Battle-Lemarie wavelets need to be investigated further.

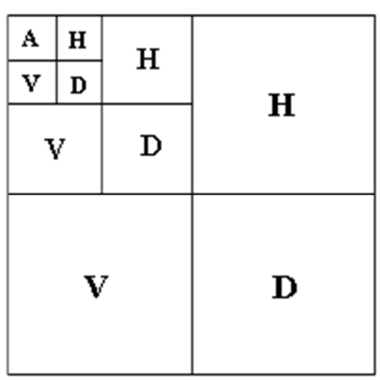


Figure 1. Wavelet decomposition of an image: three-levels

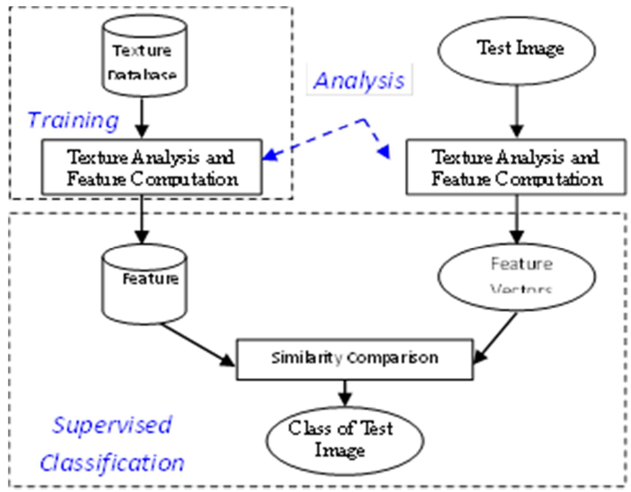


Figure 2. Block diagram of the system

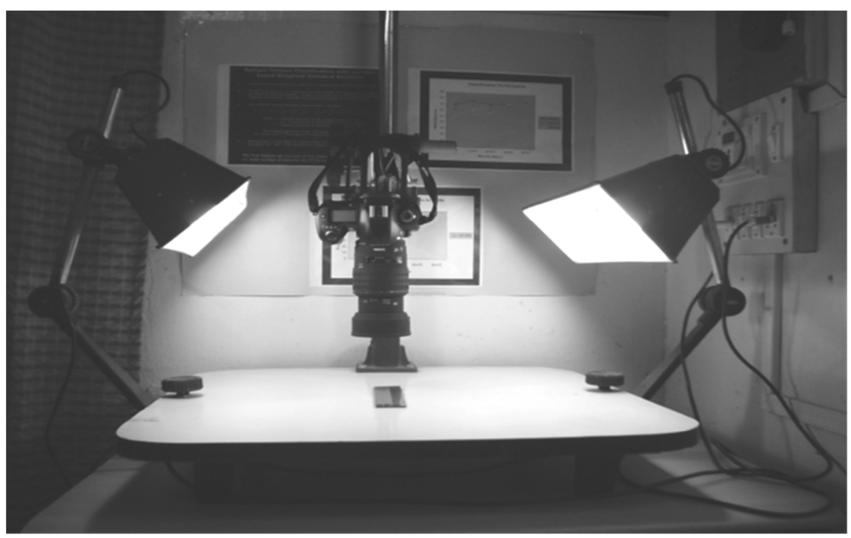
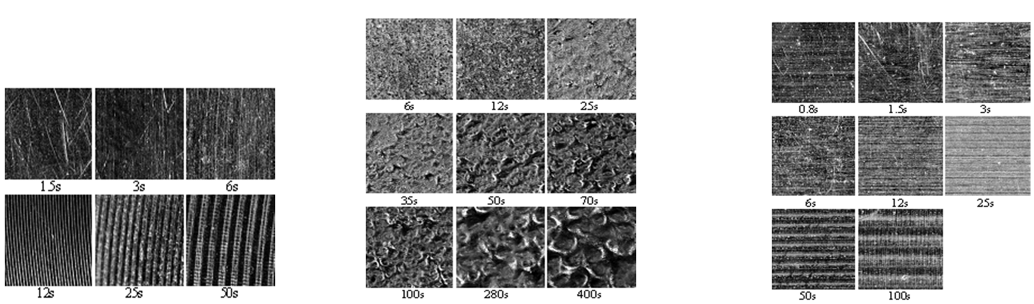


Figure 3. Experimental set-up for Image Acquisition



(a) (b) (c)

Figure 4. Texture databases

(a) Milling DB Classes (b) Casting DB Classes (c) Shaping DB Classes

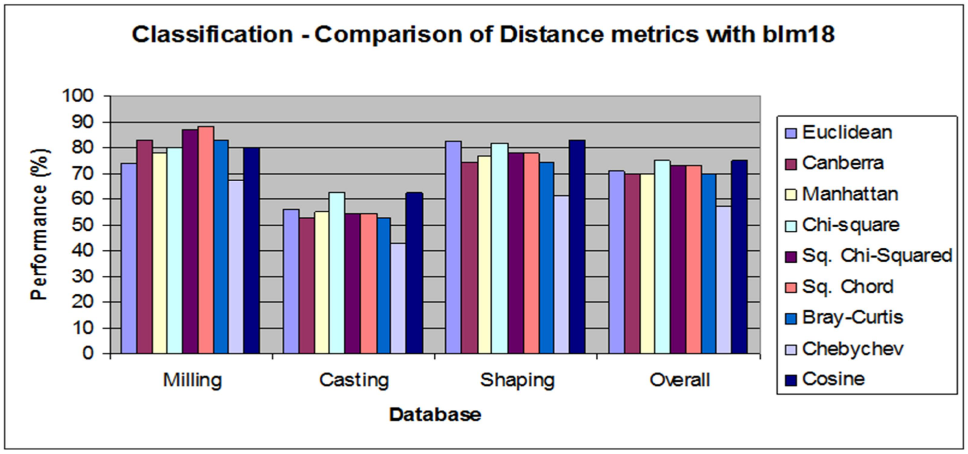


Figure 5. Classification performance of nine distance metrics with blm18 wavelet base and WSD

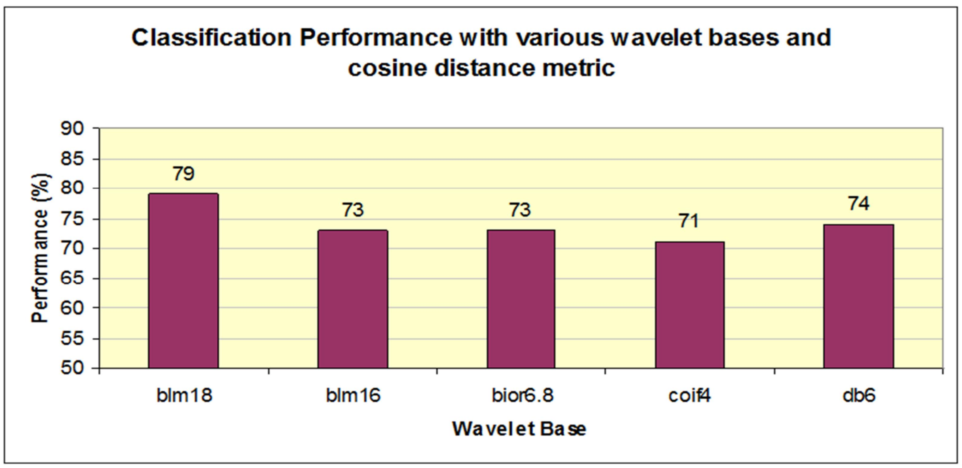


Figure 6. Comparison of classification performance of different wavelet bases with cosine distance metric (Texture descriptors: WSD+Entropy+Kurtosis)

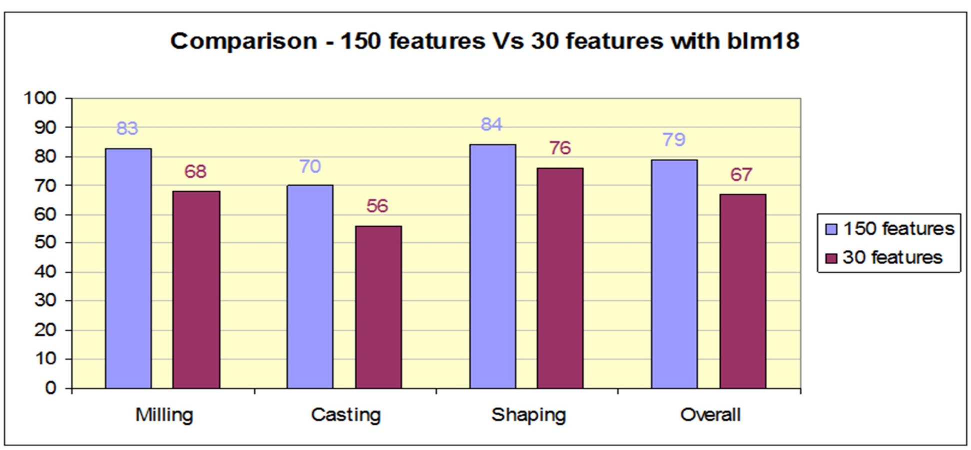


Figure 7. Comparison of performances with change in number of features (Texture descriptors: WSD+Entropy+Kurtosis)

Table 1. Performance comparison of various texture descriptors with blm18 and cosine distance metric

Texture Descriptor [Number of features]	Performance (%)			
	Milling DB	Casting DB	Shaping DB	Overall
SD [50]	79	54	76	70
WSD [50]	80	62	83	75
Energy [50]	52	46	55	51
Entropy [50]	85	53	76	71
Kurtosis [50]	76	56	73	68
WSD + Kurtosis [100]	84	65	81	77
WSD + Entropy + Kurtosis [150]	83	70	84	**79**

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References

[1] N. Bonnel de Longchamp, Surface Metrology – Web Review

[2] ASME B46.1, 1995, Surface Texture (Surface Roughness, Waviness and Lay).

[3] X. Chen, J. Raja, S. Simanapalli, “Multi-scale analysis of engineering surfaces”, Int. J. Mach. Tools Manufact, Vol. 35, No.2, pp. 231-238, 1995

[4] Chen X., “Space-frequency analysis of engineering surfaces”, M.S. Thesis, University of North Cardina at Charlotte, 1994

[5] Shengyu Fu, B. Muralikrishnan, J. Raja, "Engineering Surface Analysis with different wavelet bases", Trans. of ASME, vol 125, pp. 844-852, Nov. 2003.

[6] S. Bhagavathy, K. Chhabra, "A wavelet-based Image retrieval system", ECE 278A Project Report

[7] D. Randall Wilson, Tony R. Martinez, "Improved Heterogeneous Distance Functions", Journal of Artificial Intelligence Research, Jan. 1997

[8] Kokare, M., Chatterji, B.N., Biswas, P.K., "Comparison of Similarity Metrics for Texture Image Retrieval", TENCON 2003 Conference on Convergent Technologies for Asia-Pacific Region, Volume 2, Issue, pp. 571-575, Oct. 2003.