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(Research Article)

# Feature Extraction for Texture classification – An Approach with Discrete Wavelet Transform

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**Abstract**

Texture is used in many areas such as remote sensing, surface detection, biomedical image processing etc. Surface metrology with image processing is a challenging task having wide applications in industry. Surface roughness can be evaluated using texture classification approach. In this paper concentrated on Multi-scale multi dimensional technique for classification. Features which are included for classification of surface are Wavelet Statistical Features (WSF) and Wavelet co-occurrence Features (WCF). Important aspect here is appropriate selection of features that characterize the surface. Multi-directional transform for fast and robust feature extraction, where scale and angular decomposition properties are integrated to increase its texture classification performance. Here DWT is used for detecting surface feature. By selecting appropriate features, classification rate can be enhanced.

*Keywords*: - texture classification, feature extraction, WSF, WCF

## 1. Introduction

The important task in texture classification is to extract texture features which are most completely describing the information of texture in the image. Previously, statistical and structural approaches are used for feature extraction. Statistical approaches can represent the texture image as set of mathematical procedures to analyze the spatial distribution of the grey values in a texture image. This method preferred when image have homogeneous purely random micro texture fields, but this method cannot handle more structured macro textures. The structural methods represent a texture pattern by its textural primitives and their spatial placement rules. The main deficiency of the structural methods is that they are incapable of capturing or generating the randomness that natural textures often possess.

Various kinds of texture analysis methods are used to examine textures from different perspectives. Individual method can’t be used for all textures multidimensionality of perceived texture [8]. In the model-based approach, a set of parameters which are driven from the variation of pixel elements of texture are used to define an image model.

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The two models methods used in this work are the Gaussian Markov random field and discrete wavelet transform.

## 2. Discrete Wavelet Transform

DWT can be performed by iteratively filtering a signal or image through the low-pass and high-pass filters, and subsequently down sampling the filtered data by two. This process will decompose the input image into a series of sub band images.

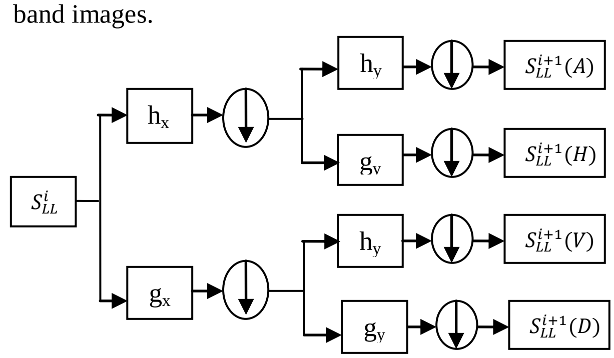


**Figure 1:** Discrete wavelet transform

Figure 1 illustrates an example of DWT, where h and g represent the low-pass and high-pass filter respectively, while the symbol with a down arrow inside a circle represents the down sampling operation. From figure 1, an image S at resolution level i was decomposed into four sub band images after going through one stage of decomposition process. The four sub band images consist of one approximation image and three detail images. The approximation image is actually the low-frequency

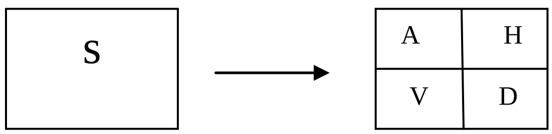


**Figure 2:** Sub band images for one level of image decomposition using DWT

Detail image contains the information of specific scale and orientation. This means that the spatial information is also retained within the sub band images (Hiremath and Shivashankar, 2006). Therefore, the detail images are suitable to be used for deriving a set of texture features in the input image. On the other hand, the approximation image can be used for higher levels of decomposition for the input image. Down sampling operation has helped to reduce the useless and redundant samples in the decomposition process. However, removing these samples will cause a translation-variant property for the decomposition results.

### 3. Proposed Approach

Texture Recognition System Figure 3 illustrates the proposed Texture analysis system. This system is composed of two sub-systems or components:
(i) Texture database
(ii) Texture recognition function

*3.1 Texture Database:* Database contain texture name, type and feature vector. Here we take three databases namely milling, casting and shaping. Each database contains six classes. First each texture name, texture type and 2D wavelet statistical feature vector and occurrence feature is stored for wavelet texture database. This feature database is used in classification stage.

*3.2 Texture Recognition Function:* This function calculates and stores the feature vectors of training images. It also calculates feature vectors of the query image and compares with the feature vectors of training images. It classifies the query image.

*3.3 Texture Features:* 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.

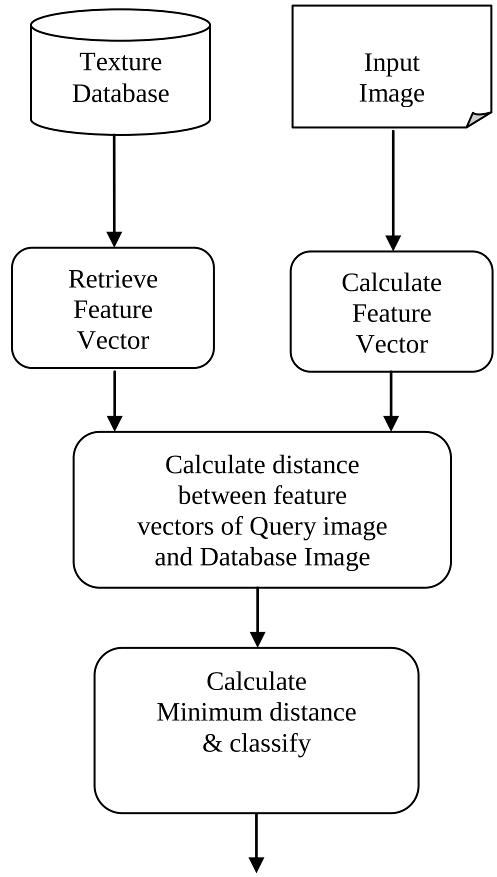


**Fig.3** Proposed Texture Recognition System

Algorithm for texture analysis and feature extraction with DWT:

- Subject the gray scale texture image to an L-level wavelet transforms decomposition.
- At each level (i=1, 2 …L), find the feature vector by using the following parameter.

*3.4 Wavelet Statistical Features:* The DWT decomposition of the image is applied up to third level. Wavelet Statistical Features for each level, for each sub band (High-High, High-Low, Low-High, Low-Low) are calculated.

i. Mean: The mean is measurement of average intensity level in that sub band.

$$\text{mean} = \frac{1}{N^2}\sum_{i,j=1}^{N} C(i,j) \qquad (3.1)$$

Where $C(i,j)$ is the transformed value in $(i,j)$ for any sub-band of size N x N

ii. Standard Deviation: The standard deviation of the image gives a measure of the amount of detail in that sub band.

$$\mathrm{SD} = \sqrt{\frac{1}{N^2}\sum_{i,j=1}^{N}[\,C(i,j) - m]^2} \tag{3.2}$$

*3.5 Wavelet Co occurrence Feature:*

i. Energy: Energy is used to measures the number of repeated pairs. The Energy is expected high if the occurrences of repeated pixel pairs are high. Energy is computed as follows,

$$\mathrm{Energy} = \sum_{i,j=1}^{N} C^2\,(i,j) \tag{3.3}$$

ii. Entropy: Entropy measures the randomness of a gray-level distribution. The Entropy is expected high if the gray levels are distributed randomly throughout the image

$$\mathrm{Entropy} = -\sum_{i,j=1}^{N} C(i,j)\,\log_2 C(i,j) \tag{3.4}$$

We use supervised classification method. So we need to define the texture classes first. We used three texture databases namely Milling, Casting and Shaping. Each database has six 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.

## 4. Texture Classification

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

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 jth texture feature of the test sample X and $f_j(k)$ is the jth texture feature of kth texture class in the database, then the Euclidean distance metrics are described as below:

Euclidean metric

$$d_E(K) = \sqrt{\sum_{j=1}^{N}\left[f_j(x) - f_j(k)\right]^2} \tag{4.1}$$

## 5. 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.). Milling database, Casting database and shaping database has six classes. One image from each class in the database can be seen in Fig4~6. Label associated with an image indicates surface roughness value. For each class we are having thirty gray scale images. Thus for milling, casting and shaping 180 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 as analysis tools. The classification performance is the rate of correct classification of surface textures. Euclidean distance measures are used. The classification results using Euclidian distance matrix with various combinations of texture descriptors are summarized in Table I.

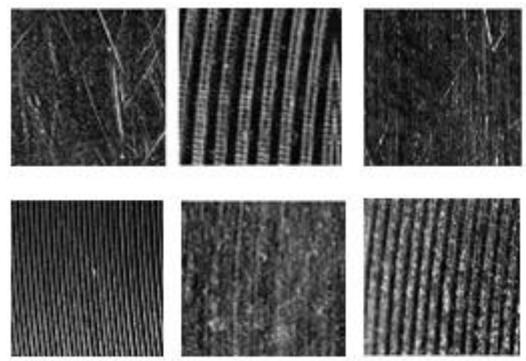

**Fig 4**. Milling database

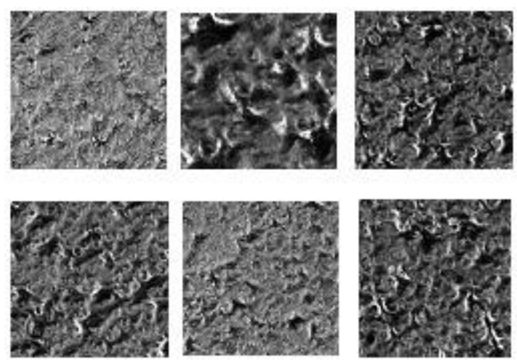

**Fig 5.** Casting database

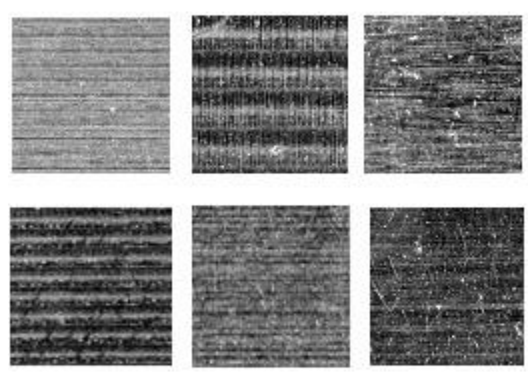

**Fig 6.** Shaping database

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**TABLE I:** CLASSIFICATION PERFORMANCE DWT WITH DIFFERENT TEXTURE DESCRIPTORS

| TD / class | SD | energy | entropy | SD+ entropy | SD+ energy | energy+ entropy | SD+ entropy+ energy |
|---|---|---|---|---|---|---|---|
| Mill 1s | 73.33 | 63.33 | 90.00 | 83.33 | 80.00 | 100.00 | 86.67 |
| Mill 4s | 76.67 | 100.00 | 80.00 | 86.67 | 90.00 | 90.00 | 100.00 |
| Mill 8s | 60.00 | 83.33 | 70.00 | 100.00 | 86.67 | 100.00 | 96.67 |
| Mill 16s | 93.33 | 96.67 | 80.00 | 96.67 | 90.67 | 83.37 | 100.00 |
| Mill 32s | 96.67 | 60.00 | 96.67 | 100.00 | 70.00 | 80.00 | 93.33 |
| Mill 64s | 83.33 | 100.00 | 100.00 | 93.33 | 83.67 | 86.67 | 96.67 |
| Milling DB | 80.55 | 83.88 | 86.11 | 93.33 | 83.50 | 90.00 | 95.55 |
| Cast 6s | 70.00 | 73.33 | 80.00 | 83.33 | 86.66 | 80.00 | 90.00 |
| Cast 12s | 73.33 | 60.00 | 70.00 | 79.33 | 70.00 | 73.33 | 96.00 |
| Cast 25s | 80.00 | 70.00 | 86.67 | 86.67 | 73.33 | 80.00 | 86.67 |
| Cast 34s | 76.67 | 76.67 | 66.67 | 73.33 | 80.00 | 86.67 | 80.00 |
| Cast 50s | 60.00 | 80.00 | 76.67 | 90.00 | 60.00 | 83.33 | 76.67 |
| Cast 60s | 76.67 | 80.00 | 90.00 | 83.37 | 86.66 | 76.67 | 100.00 |
| Cast DB | 72.77 | 73.33 | 78.33 | 82.67 | 76.10 | 80.00 | 88.22 |
| Shape 0.4s | 76.67 | 100.00 | 86.67 | 100.00 | 83.33 | 100.00 | 100.00 |
| Shape 0.8s | 80.00 | 80.00 | 70.00 | 90.00 | 80.00 | 96.67 | 96.67 |
| Shape 1s | 73.33 | 96.67 | 80.00 | 100.00 | 86.67 | 90.00 | 93.33 |
| Shape 1.5s | 73.67 | 96.67 | 83.33 | 83.37 | 96.67 | 96.67 | 100.00 |
| Shape 4s | 60.00 | 86.67 | 100.00 | 80.00 | 100.00 | 93.33 | 96.67 |
| Shape 12s | 80.00 | 86.67 | 90.00 | 86.67 | 80.00 | 90.00 | 93.33 |
| Shape DB | 73.94 | 91.11 | 85.00 | 90.00 | 87.77 | 94.44 | 96.67 |
| Overall performance | 75.75 | 82.77 | 83.14 | 88.60 | 82.46 | 88.15 | 93.48 |

We carried out experiment with DWT [6] as an analysis tool and the with texture descriptors which is describe in previous section. We carried out 3-level DWT decomposition of original 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, energy and entropy of original image. Thus the length of the feature vector is 5 images * [3 texture descriptors * (3 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.

## 6. Conclusion

DWT extracts information in horizontal, vertical and diagonal orientations. We tried to improve performance of DWT by using different parameter for feature extraction. In case of DWT, when SD, energy and entropy are used separately as texture descriptors we got the performances as 75.75%, 82.77% and 83.14% respectively. Our experiments suggest that the combination of these three descriptors is useful to categorize surfaces with their roughness values with the performance of 93.48%.

These texture descriptors which are used in our application are very effective. 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, grit blasting, hand filing, linishing, shot blasting etc. Our future study will also undertake the work regarding computation of efficiency of these approaches.

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