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TEXTURE CLASSIFICATION BASED ON GABOR WAVELETS

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Abstract: *This paper presents the comparison of Texture classification algorithms based on Gabor Wavelets. The focus of this paper is on feature extraction scheme for texture classification. The texture feature for an image can be classified using texture descriptors. In this paper we have used Homogeneous texture descriptor that uses Gabor Wavelets concept. For texture classification, we have used online texture database that is Brodatz's database and three advanced well known classifiers: Support Vector Machine, K-nearest neighbor method and decision tree induction method. The results shows that classification using Support vector machines gives better results as compare to the other classifiers. It can accurately discriminate between a testing image data and training data.*

Keywords: *Texture Classification, MPEG-7 Homogeneous texture descriptor, Gabor Wavelets, Support Vector Machine, K-nearest neighbor classifier, decision tree induction method.*

I. INTRODUCTION

Texture is a measure of variation of intensity of surface, quantifying properties such as smoothness, coarseness and regularity. Texture characterizes the local properties of the gray level of an image region and plays an important role in many image processing tasks such as content based image retrieval ,computer vision ,medical imaging. Natural textures are random, whereas artificial textures are often deterministic or periodic. Figure 1 shows different types of texture fields.

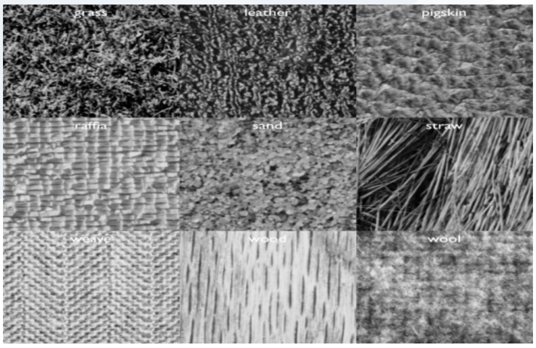


Figure 1: Different types of textures

There are three main ways textures are used:

1. To discriminate between different (already segmented) regions or to classify them,
2. To produce descriptions so that we can reproduce textures, and
3. To segment an image based on textures.

In image analysis, texture is classified into two main categories, statistical and structural. In Statistical approach texture is random in nature [9]. It characterizes texture by the statistical properties of the grey levels of the points comprising a surface. These properties are computed from grey level (histogram) or grey level of the surface. In Structural approach, Structural textures are deterministic texels, which repeat according to some placement rules, deterministic or random. The placement rules define the special relationships between the texels, these special relationships may be the adjacency, closest distance and periodicities. Different approaches have been taken for texture representation, such as: texture descriptors based on co-occurrence matrices and random field texture models, multi-resolution techniques using Gabor and wavelet filters and local edge histogram descriptor of an image [5].

There are three descriptors of texture feature of a region. First is homogeneous texture descriptor (HTD), the edge histogram descriptor(EHD), and the perceptual browsing descriptor (PBD).These are currently included in the Committee Draft of MPEG-7 Visual (ISO/IEC 15938-3)[2].

In this paper, our concern is with texture classification using Gabor wavelets. Firstly, Texture discrimination is done to partition a textured image into regions, each corresponding to a perceptually homogeneous texture (leads to image segmentation), Secondly feature extraction is done using Homogeneous texture descriptor that is vector of 62 numerical features coming from Gabor Wavelets. For texture classification, we have used online texture database that is Brodatz's database and three advanced well known classifiers: Support Vector Machine, K-nearest neighbour method and decision tree induction method.

Lastly, the accuracy and performance is measured using, precision, true positive rate and false positive rate.

II. TEXTURE DISCRIMINATION

A. General Steps for Texture representation

Texture Discrimination

↓

Texture feature Extraction

↓

Texture Classification

Figure 2: Steps for Texture Representations

Step 1. Texture discrimination is to partition a textured image into regions, each corresponding to a perceptually homogeneous texture (leads to image segmentation).

Step 2. Texture feature extraction is to compute a characteristic of a texture image that is able to numerically describe its texture properties. 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 [Awcock95].

Step 3. Texture classification is to determine to which of a finite number of physically defined classes (such as normal and abnormal tissue) a homogeneous texture region belongs. If the classes have not been defined a priori, the task is referred to as unsupervised texture classification. On the other hand, if the classes have already been defined through the use of training textures, then the process is referred to as supervised texture classification.

In our research, only supervised texture classification is considered and classification accuracy can refer to the percentage of correctly classified texture samples.

B. Partitioning of texture images using MATLAB

Following are the texture images from six classes from Brodatz's database [29] namely:

Table 1: Six classes from A to F

Texture Class	*Class name*	*Sample Size before partitioning*
Class A	Grass (1.1.01)	512 x 512
Class B	Wood (1.1.02)	512 x 512
Class C	Straw (1.1.03)	512 x 512
Class D	Brick (1.1.12)	512 x 512
Class E	Weave (1.1.04)	512 x 512
Class F	Animal Skin (1.1.06)	512 x 512

C. Texture images with 512 x 512 sample size

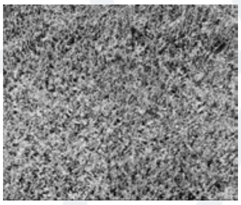
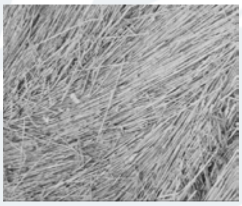
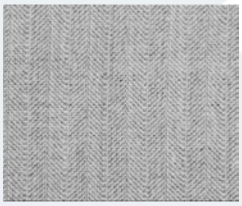
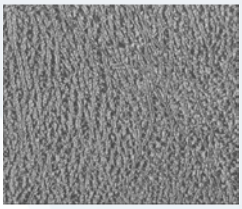
S. No	*Texture Images*	*Texture Image Name*
1.		Grass (A)
2.		Wood (B)
3.		Straw (C)
4.		Weave (D)
5.		Animal Skin (E)
6.		Brick (F)

Figure 3: Texture images used for Experiment

These image classes (512 x 512) are further sub-partitioned into 16 (128 x 128, 64 x 64 and 32 x 32) sample sizes, making total of 288 (96+96+96) texture images. These images further used for texture feature extraction and texture classification process.

III. HOMOGENEOUS TEXTURE DESCRIPTOR

The feature extraction is done using homogeneous texture descriptor (HTD). The HTD describes a statistical distribution of the image texture. It's a vector of 62 integers coming from the Gabor filter response of 30 frequency layout channels which enables to classify images with high precision. HTD is to be used for similarity retrieval application [7].

The HTD provides a quantitative characterization of texture for similarity-based image-to-image matching. This descriptor is computed by first filtering the image with a bank of orientation and scale sensitive filters, and computing the mean and standard deviation of the filtered outputs in the frequency domain [4].Previous extensive work on this feature descriptor has shown that this descriptor is robust, effective, and easy to compute [4].

MPEG-7 HTD is obtained by filtering the image with bank of 30 orientations (6 different) and scale (5 different) sensitive Gabor filters. The mean and standard deviation of filtered images are calculated in frequency domain .Additionally mean and standard deviation of original image is computed as well, resulting in a feature vector of 62 values [6].

Manjunath and Ma [3] have shown that image retrieval using Gabor features outperforms that using pyramid-structured wavelet transform (PWT) features, tree-structured wavelet transform (TWT) features and multiresolution simultaneous autoregressive model(MR-SAR) features. Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction. Expanding a signal using this basis provides a localized frequency description, therefore capturing local features of the signal. Texture features can then be extracted from this group of energy distributions. The scale (frequency) and orientation tunable property of Gabor filter makes it especially useful for texture analysis [3].

A. Feature Representation

HTD sets S as 5 and K as 6.Given an image g(x, y) with size P x Q, its Gabor wavelet transform is then defined to be [3]:

$$w_{mn}(x,y)=\iint I(x_1,y_1)g_{mn}{}^{*}(x-x_1,y-y_1)dx_1dy_1 \qquad (1)$$

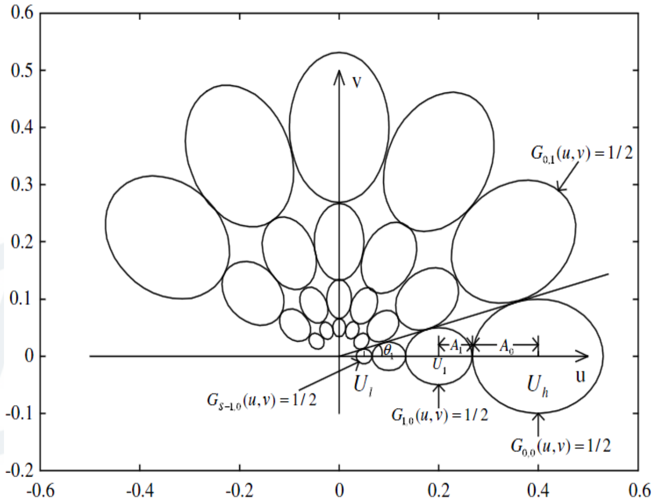


Figure 4: Frequency Domain division Layout: the contour indicates the half-peak magnitude of the filter responses in the Gabor filter dictionary. The filter parameters used in implementation are U_h= 0.3 and U_l= 0.05, K=6 and S=5.

Where * indicates the complex conjugate. It is assumed that the local texture regions are spatially homogeneous, and the mean μ_{mn} and the standard deviation $\sigma_{mn}$of the magnitude of the transform coefficients are used to represent the region for classification and retrieval purposes [3]:

$$\mu_{mn} = \frac{\iint |w_{mn}(x,y)|dxdy}{PXQ}$$

$$\sigma_{mn} = \frac{\sqrt{\iint (|w_{mn}(x,y)|-\mu_{mn})2dxdy}}{PXQ} \qquad (3)$$

The mean and standard deviation of original image are defined as follows:

$$\mu_{sd} = \frac{\iint |I(x,y)|dxdy}{PXQ}$$

$$\sigma_{sd} = \frac{\sqrt{\iint (|I(x,y)|-\mu_{sd})2dxdy}}{PXQ}$$

So MPEG-7 HTD can be represented by a 62-dimentional vector as:

$$f = \{\mu_{sd}, \sigma_{sd}, \mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \dots \dots \dots \dots, \mu_{45}, \sigma_{45}\} \qquad (6)$$

After feature extraction, the next step is the classification of texture database .So that we can discriminate between different-2 texture classes category-wise.

IV. TEXTURE CLASSIFICATION

Classification refers to as assigning a physical object or incident into one of a set of predefined categories. In texture classification the goal is to assign an unknown sample image to one of a set of known texture classes. The texture classification methods based on MPEG-7 homogeneous texture descriptor for better and accurate results. The implementation of first part that is feature extraction of texture classes is done using MATLAB7 software and texture classification is done by using java based Weka-Tool [1].

Texture classification is to determine to which of a finite number of physically defined classes (such as normal and abnormal tissue) a homogeneous texture region belongs. If the classes have not been defined a priori, the task is referred to as unsupervised texture classification. On the other hand, if the classes have already been defined through the use of training textures, then the process is referred to as supervised texture classification. Three classification methods namely Support Vector Machine classifier, K-nearest Neighbour methods and Decision tree induction are applied to classify training and testing data.

In our work, only supervised texture classification is considered and classification accuracy can refer to the percentage of correctly classified texture samples.

V. PROPOSED ALGORITHM

A. Steps for Implemented Algorithm

Step 1. Texture feature extraction.

For each orientation K, calculate total energy of S scales.

For i=0 to K-1 //K=6, 6 orientation

For j=0 to S-1 // S=5, 5 scales

Energy[i] = Energy[i] $+\mu_{ji}$; //mean energy at 30 orientations

Sd [i] = Sd [i] $+\mu_{ji}$; // standard deviation at 30 orientations

Then it gives MPEG-7 HTD of 62-dimentional vector:

f= $\{\mu_{sd}, \sigma_{sd}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots\ldots\ldots\ldots\ldots\ldots, \mu_{45}, \sigma_{45}\}$

Step 2. First done texture Classification using SVM where convert the above feature vector into CSV format (Comma Separated values).In this way , all the training and testing data can also be converted and ready to use for classification.

Step 3. Then apply RBF kernel and use cross validation to find best parameter C and γ.

Step 4. Use the best parameter C and γ to train the whole dataset.

Step 5. Classified the testing data.

Step 6. Again in Second step, used KNN classifier and Decision tree induction methods for classification in the place of SVM Classifier.

B. Design of Experiments

As shown in Table 2, three types of experiments are designed to illustrate the efficiency and effectiveness of the proposed method.

Table 2: Experiments and their procedures

Experiment Name	*Procedures*
HTD + SVM	Use above Algorithm 5.1
HTD+ KNN	In Algorithm 5.1,Use KNN as classifier method.(K=31)
HTD + DT	In Algorithm 5.1, Use Decision tree induction method (C 4.5).

Where, HTD is the Homogeneous texture descriptor. The experiments were carried out on a PC equipped with i3 2.27GHZ CPU and 3 GB RAM. The Gabor wavelet for feature extraction is implemented in the MATLAB environment. The implementation of SVM (Support Vector Machine), KNN (K Nearest Neighbour) and decision tree induction method (C 4.5) is done using WEKA data miner.

VI. IMAGE CLASSIFICATION RESULTS

Finally the results have been demonstrated in the form of graphs. All the classification techniques have been tested on texture images from Brodatz's dataset from the USC-SIPI image database [8].

A. Graphical Representation of Results

The performance of each classifier is measured using the conventional micro-averaged precision, macro-averaged precision and true positive and false positive rate. In Micro-averaged, it can be first computed for individual classes and in the case of Macro-averaged, average of all classes as a global measure can be evaluated.

1. Micro-Averaged Precision on 128 x 128 sample *size data*

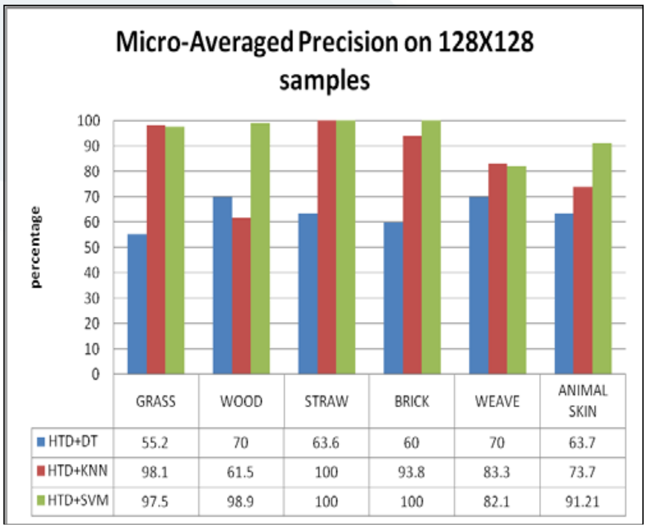


Figure 5: Micro-averaged precision on 128 x 128 sample images.

Figure 5 shows that SVM is very effective on the images whose texture contain lots of straight lines, such as grass, wood, straw and brick. However classification rate in images like weave and animal skin are less.

2. Micro-Averaged Precision on 64 x 64 Sample size data

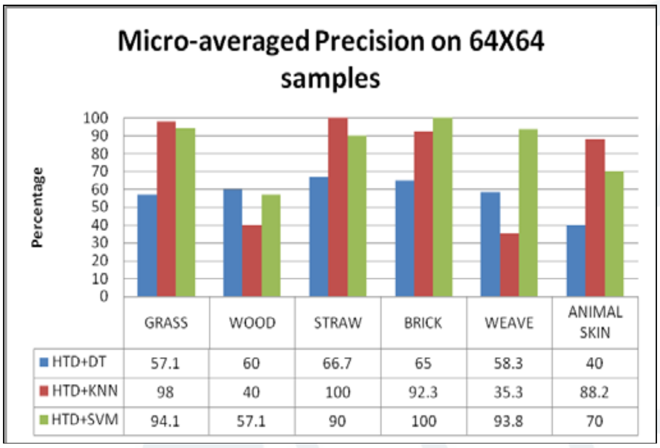


Figure 6: Micro-averaged precision on 64 x 64 sample images.

3. Micro-Averaged Precision on 32 x 32 Sample size data

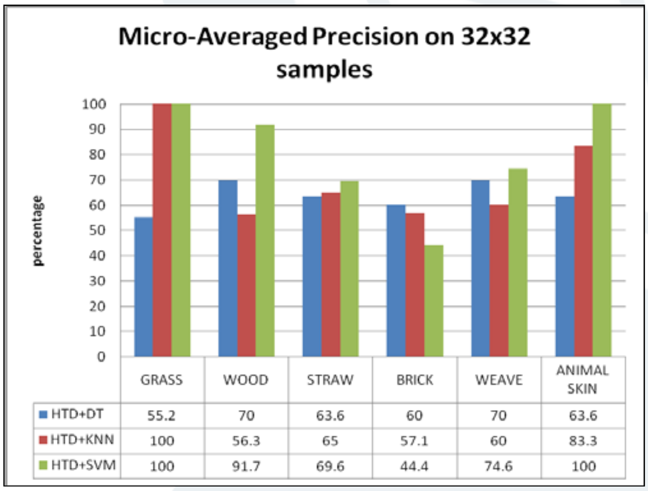


Figure 7: Micro-averaged precision on 32 x 32 sample images.

4. Macro-Averaged Precision

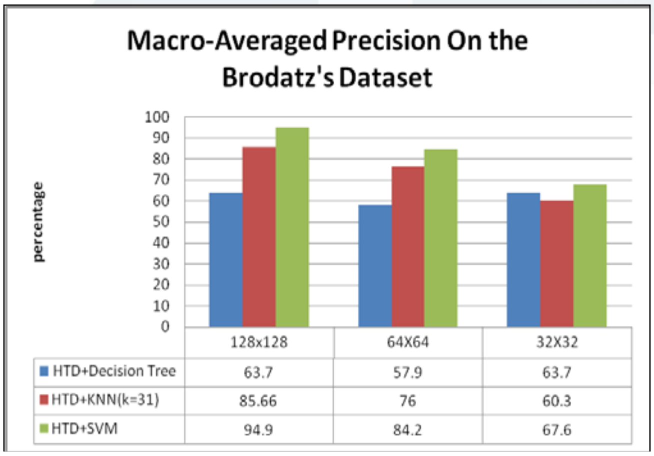


Figure 8: Macro-averaged precision

Figure 5, 6, 7 and 8 demonstrate that higher precision can be achieved if size of sub images is larger. The 32 x 32 samples contain only one sixteenth of the pixel data as compare to 128 x 128 samples, consequently the feature vectors possess less discriminative power. Here it is observed that method based on SVM performs significantly better results than KNN and Decision tree induction method.

5. True Positive Rate

A true positive is when the outcome is correctly classified as "yes" (or "positive").

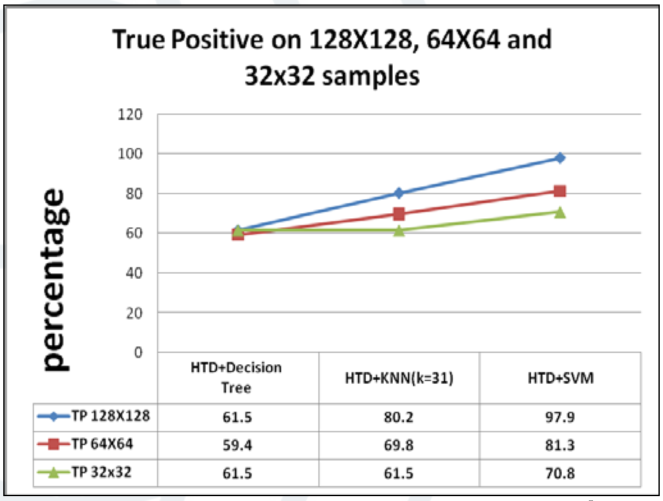


Figure 9: True positive Rate on 128 x 128, 64 x 64 and 32 x 32 sample size data.

6. False Positive Rate

A false positive is when the outcome is correctly classified as "yes" (or "positive"), when it is in fact "no" (or "negative").

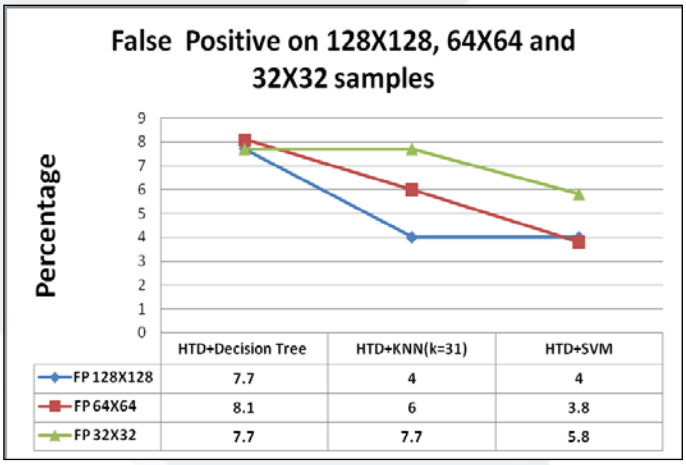


Figure 10: False positive Rate on 128 x 128, 64 x 64 and 32 x 32 sample data.

Figure 9 shows that true positive rate on 128 x 128 sample size is more as compare to the 64 x 64 and 32 x 32 samples. And figure 10 shows that false positive rate on 64 x 64 and 32 x 32 sample size is more as compare to the 128 x 128 sample size.

VII. CONCLUSION AND FUTURE WORK

The current research deals with the problems of texture retrieval using homogeneous texture descriptors and texture classification using support vector machine classifier, K-nearest neighbour classifier and decision tree induction classifier. The results show that classification using Support vector machines shows better results as compare to the other classifiers. It can accurately discriminate between a testing image data and training data.

The performance evaluation of three classifier shows that macro-averaged precision on 128 x 128 sample images shows better results as compare to 64 x 64 sample images.

1. In the case SVM classifier ,**128** x **128 gives 94.9 % accuracy rate** whereas 64 x 64 samples give 84.2% and 32 x 32 samples give 67.6%
2. In the case KNN classifier ,**128** x **128 gives 85.66 % accuracy rate** whereas 64 x 64 samples give 76% and 32 x 32 samples give 60.3%
3. In the case decision tree (C 4.5) ,**128** x **128 gives 63.7% accuracy rate** whereas 64 x 64 samples give 57.9% and 32 x 32 samples give 63.7%
4. Figure 5 shows that SVM is very effective on the images whose texture contain lots of straight lines, such as grass, wood, straw and brick. However classification rate in images like weave and animal skin are less. In the case of brick it is 100%.
5. Figure 5, 6, 7 and 8 demonstrate that higher precision can be achieved if size of sub images is larger. The 32 x 32 samples contain only one sixteenth of the pixel data as compare to 128 x 128 samples, consequently the feature vectors possess less discriminative power. Here it is observed that method based on SVM performs significantly better results than KNN and Decision tree induction method.
6. True positivity is more in the case of SVM 128 x 128 sample data and has less false positivity.

Future work can be extended on designing improved texture feature representations to obtain Scale invariance and illuminance invariance image classification on grey and coloured images.

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