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Machine Learning Based Surface Material Classification System

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Abstract* — Natural Texture such as surface of materials has a complicated structure. There is no appropriate standard to describe features at present. Describing and classifying natural texture surface is an important issue in the field of computer vision. Several machine learning algorithms have been existed to distinguish texture surfaces but most of them are suitable to only particular class of surfaces. There are no sufficient numbers of works on six classes such as Tiles, Leather, Wood, Plywood, Metal and Textile fabrics surfaces. Wavelet features by Discrete Wavelet Transform (DWT) and Texture features by Gray Level Co-occurrence Matrix (GLCM) have shown efficient results in other fields so it is concluded to use these features for classification of material surfaces. The proposed methodology is evaluated on data set of 6 class surfaces such as Tiles, Leather, Metal, Wood, Fabrics, Plywood images, each class contains 20 different samples for training and 5 samples of each class which are completely different from training samples are taken for testing. The system achieved classification rate of 95.33% which is satisfactory from previous works.

Keywords- Pre-processing; Binarization; Normalization; Feature Extraction; Classification

I. INTRODUCTION

Texture is one of the precise concepts. Each material surface exhibits different kinds of properties like friction, shapes, color and size, internal structures etc. A human can recognize or classify the material surface based on their strategies such as by vision, touching the surface and by observing sound produced. Implementing human kind of perception in image processing technology is a complex task as each images of a particular class of surfaces exhibits different properties. Even images of one class exhibits similar properties of other class. Machine Learning Based surface material classification system scans the surface images and classify the images in database model in order to outline those images into particular matching class. There are many existing machine learning algorithms are proposed to classify the surface images with sensible levels of accurateness.

Nowadays in the field of Medical, Photography, Satellite, Microscopic image processing, surface classification technology plays an important role. The machine learning based surface material classification system comprises of different challenges/issues since all images in particular surface class are different in their color, shapes and their internal structure as shown in Figure 1.1 Some of the images in Figure 1.2 (a), (b) shows two different classes which exhibits similar properties.

Figure 1.1 In Tile class each tile surfaces exhibits different color, design, shape.

(a) *(b)*

Figure 1.2 (a) Leather surface. (b) Metal surface.

The task is more difficult as each material typically exhibit huge intraclass and small interclass unevenness and there is no extensively applicable yet mathematically precise models which report for such transformations. The job is made even further challenging if no a prior information about the imaging conditions which are available. A texture image is one of the primary functions of the following variables: the texture surface, illumination, camera and its screening location. Even if we were to maintain the initial two parameters constant, i.e. photograph precisely the same piece of texture each time, minor variations in the other parameters can direct to dramatic variations in the resultant image. This leads to a large variation in the imaged manifestation of a texture and dealing with it successfully is one of the prime jobs of any classification algorithm. Another aspect which comes into play is the reality that is somewhat often, two materials when captured under very dissimilar imaging situation can appears to be quite similar. Surface material classification has earned significance in past few years as the media engineering continues to develop. Unluckily most existing natural surface material classification schemes tends to work properly with only few selected classes of surface materials over a inadequate variety of imaging conditions, but some time they may not work properly when viewpoint and illumination vary extensively. Since many experimentations are going on to construct an efficient and robust surface material classification system to conquer the challenges such as variation in images of single class and similarities between images of two different surface classes. Many methods have been proposed to classify the material surfaces in single class of surface. In many of existing system, devices like sensors, robots were used to recognize and classify the different material surfaces. Neural network comprise rapid training/learning rate because of their local-tuned functional and computational units, neurons. They have also exhibits universal approximation property and have better generalization ability. Thus the proposed system employs soft computing tool an artificial neural network (ANN). It involves 6 classes of natural material surfaces such as Leather, Tiles, Wood, Metals, Textile Fabrics, and Plywood. Each surface class includes 20 different samples of a particular class.

1.1 Objectives

The objective is to develop an efficient classification system which can accurately classify six classes of surfaces which takes surface image as an input for classification. More specifically objectives of proposed system are as follows:

- To develop Classification system which commonly comprises a series of sequential operations, including atmospheric correction or normalization and illumination correction for image enhancement.
- To develop feature extraction module this yields a classification of each material surface class in terms of feature measures. It is important to identify and select distinguishing features that are invariant to irrelevant transformation of the surface image.
- To develop Classification module can reliably and accurately discriminate among a six different natural material surface classes such as Tiles, Plywood, and Woods, Fabrics, Leather, and Metal surfaces.

II. LITERATURE SURVEY

From the literature survey it is come to know that the surface classification is a complicated task and the classification technique is rarely found. The proposed system uses machine learning technique for classification of six material surface classes. The proposed approach is one of such efficient method for surface classification by exploiting the information conveyed by multiple modalities.

2.1 Issues identified

- *Variations in object illumination:* Each material surface exhibits diverse range of light illuminations. It is hard to define appearance of a material surface based on their visual impression. The variation in surface illumination relies on the object's shape at various scales, on its material properties, and on the illumination environment thus makes classification process more complex.

- *Dissimilarities in intraclass images:* Some surfaces exhibit different properties within the same class they may exist with difference in color, shape, size.
  Ex: Each Tile surfaces come under same class but they vary in their color shape and design pattern.

- *Similarities in interclass images:* Some surfaces exhibits same types of properties among the two different classes, surfaces may have similarities in design pattern, color, shape.
  Ex: Some of the Tile surfaces have similar pattern like plywood surfaces.

2.2 Some of the Image processing issues considered:

- *Enhancement and filtering:* This step relates to image quality improvement from a noise level or homogeneity point-of-view. Each noise filtering strategies allows only little modifications in the structures of interest or drifts or background correction.

- *Feature Extraction Method:* Here selection of feature extraction methods plays a vital role, because each images of same class exhibits different patterns and features. Selection of feature extraction methods must support performance and accuracy goal.

- *Classification method:* Selection of a classifier plays a most important role. The classifier must perform an efficient and reliable classification of different types of surface classes.

III. PROPOSED METHODOLOGY

The problem definition concluded after literature survey is to develop an efficient machine learning based surface material classification system that can accurately and reliably differentiate among six classes of material surfaces such as Tiles, Woods, Metals, Plywood, Fabrics and leather surface images regardless of their view point and illumination condition. The system ensures that it overcomes some of the pre-processing issues by selecting efficient feature methods and classifier for pattern recognition and to perform accurate classification of material surfaces. Images which have been captured under controlled illumination condition are taken as an input to the system. Initially the system can't make discrimination among the input images thus the input image undergoes some pre-processing steps which make the images suitable for classifying system to perform its operation accurately. The proposed model for this work indicated in Figure 3.1. It comprises of two phases training and testing phase. It includes a few stages which are explained in following sections.

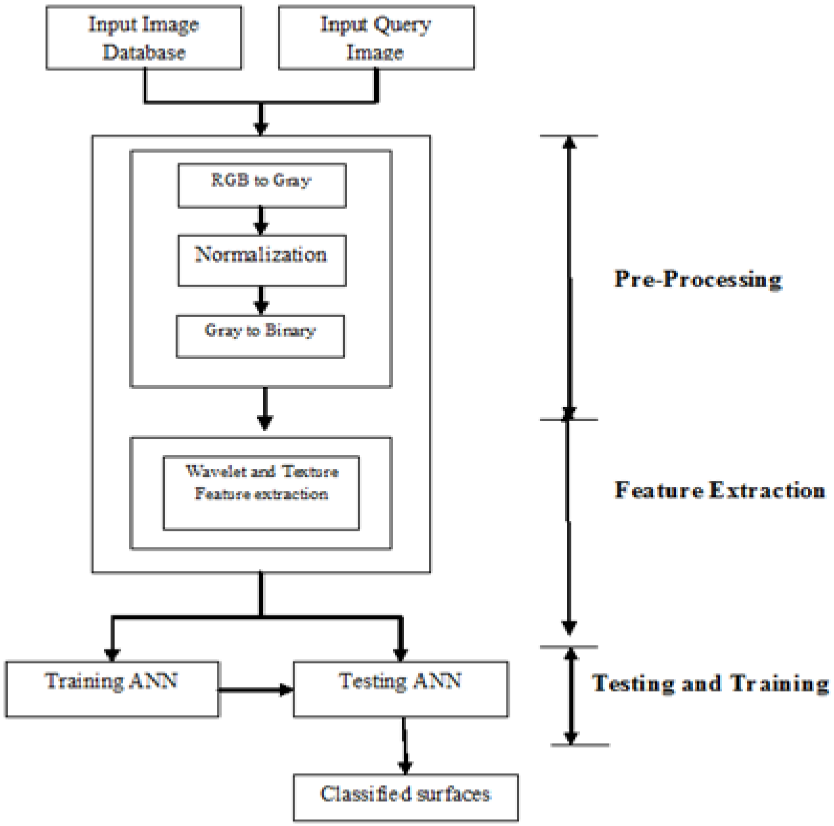

Figure 3.1 Block diagram of Proposed Model

The principle steps included in accomplishing surface material classification system are as follows:

- Pre-processing of input image
- Feature extraction
- Training
- Testing for classification

3.1 Pre-processing
At this stage the acquired image taken as an input to the system and undergoes series of pre-processing steps such as RGB to Gray scale conversion, Histogram normalization is performed on gray image for image enhancement, enhanced image and then converted in to binary image which are well suited to perform time-frequency conversion.

3.2 Feature Extraction
Extraction of the features from an image is a significant step in any surface classification system, because the classification accuracy is totally relies on feature extracted. The main goal of the feature extraction method is to exactly get back the features. In proposed system the wavelet features such as DWT and Texture features such as GLCM methods are used to extract features from input image as well as query image.

3.3 Training
This includes constructing an appropriate neural network model (BPNN). The extracted features are input to the BPNN, which classify the various types of surfaces. The neural network architecture is trained itself accordingly. The training process takes place so that the neural network builds knowledge base regarding how actually each entry in the input file has a corresponding entry at the output file. Flow chart for training BPNN is shown in figure: 3.2(a).

3.4 Testing
In this step we can get appropriate results. In testing phase input image samples from testing file is selected and its features are extracted and are handover to trained model. Then the trained BPNN classifies given samples and separates the images based on their surface class. Flow chart for testing is depicted in Figure 3.2(b).

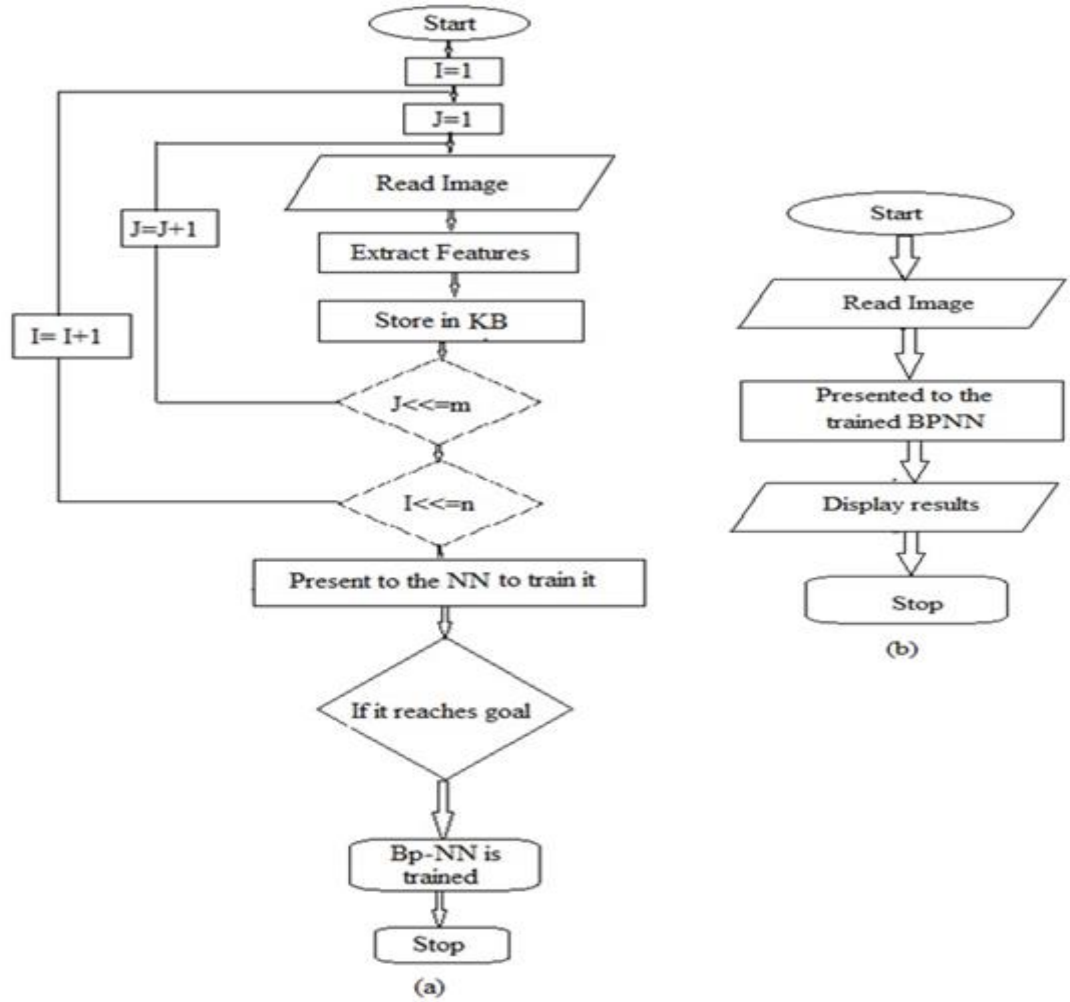

Figure 3.2 (a) Training (b) Testing flow diagram

IV. FEATURES EMPLOYED

The heart of classification system for any surface image is extracting the feature of that image. The main goal of feature extraction technique is to accurately regain the wavelet and texture based features. Feature extracted from surface images are as follows.

4.1 Discrete Wavelet Transform (DWT)

DWT can be operated by repeatedly filtering an image by using low-pass as well as high-pass filters and after down sampling the filtered image by 2. This process decomposes an input image into a sequence of sub-band images.

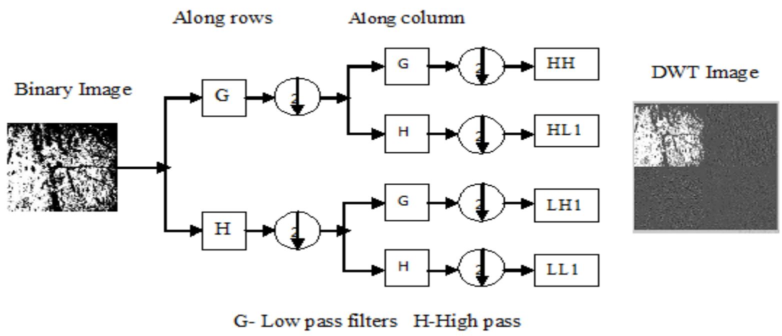

Figure 4.1: DWT model.

Figure 4.1 shows an architecture of DWT model; here H and G illustrate the low-pass and high-pass filter respectively, symbol with a (↓) down arrow inside a circle represents the "down sampling operation". In figure 4.2, an image 'S' at resolution level 'i' will be decomposed into 4 sub-band images after going through first level of decomposition process. The 4 sub-band image contains one approximation image and 3 detailed images. An approximation image is mainly the low-frequency.

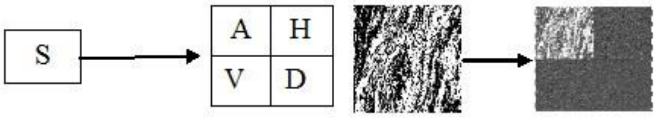

Figure 4.2 (a), (b) Image decomposition using DWT.

Detail image consist the data of specific scale as well as orientation. In fact the spatial data is also reserved inside the sub-bands. Thus, detail images are appropriate for deriving a set of texture features from input image. The approximation image can be employed for higher decomposition level for an input image. The down sampling process has helped to diminish the redundant as well as unwanted samples in the decomposition process. However, flushing out these samples will affect the translation variation properties for the decomposition results.

Steps involved in analysis and feature extraction of surface using DWT:

- Selects the gray-scale surface image to decompose it into L-level wavelet transforms.
- In each level [i=1, 2 …L] of decomposition, feature vector is identified by making use of following parameter.

The DWT decomposition of an image is applied up to third level. Wavelet Statistical Features (WSF) such as mean, variance and standard deviation (SD) for all 4 sub-bands [High-High, High-Low, Low-High, Low-Low] of each level are computed.

Mean: Average intensity level in that sub-band is calculated by using following equation.

$$\mathrm{Mean} = \frac{1}{N^2}\sum_{i,j=1}^{N} \mathrm{C(i,j)} \qquad (1)$$

Here $\mathrm{C(i,j)}$ is transformed pixel value in $(\mathrm{i,j})$ for any sub-band of size N x N.

Variance: It shows how broadly each individual group of pixels vary.

Standard Deviation (SD): It provides a measurement of the amount of information present in that sub-band and is given by following equation.

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

4.2 Texture Features

The proposed system uses GLCM feature which uses four popular features such as Energy, Entropy, Homogeneity, and Contrast for computation of texture features. Each features are calculated using following equations as shown in Table 4.3. A statistical method, which can well illustrate second-order statistics of the texture image, is called co-occurrence matrix. GLCM was introduced by Haralick. A GLCM is a 2-D histogram. It considers the spatial relationship between pixels of dissimilar gray levels. The approach computes a GLCM by calculating how two pixels i and j with certain intensity are related to each other at some distance d and orientation ϴ. Co-occurrence matrix is calculated by the relative frequencies P (i, j, d, ϴ). A co-occurrence matrix is a function of distance d, angle ϴ and gray scales 'i' and 'j'. GLCM analyzes pairs of horizontally neighbouring pixels in a scaled version of I.

Table 4.1 GLCM features

Energy	$\mathrm{F1} = \sum_{\mathrm{i,j=0}}^{\mathrm{N-1}} \mathrm{P}_{\mathrm{i,j}}^2$
Contrast	$\mathrm{F2} = \sum_{\mathrm{i,j=0}}^{\mathrm{N-1}} \mathrm{P(i,j)} * (\mathrm{i-j})^2$
Homogeneity	$\mathrm{F3} = \sum_{\mathrm{i,j=0}}^{\mathrm{N-1}} \frac{\mathrm{P(i,j)}}{1+(\mathrm{i-j})^2}$
Entropy	$\mathrm{F5} = \sum_{\mathrm{i,j=0}}^{\mathrm{N-1}} \mathrm{P(i,j)} * [-\ln(\mathrm{P(i,j)})]$

If 'I' is a binary image, it is scaled to 2 levels 8x8x2. In every sub-band 2x4 features are extracted. Thus 32 features (4x8) are extracted from one approximate image and three sub band images were produced and one set of RGB color features (3 features) are stored in combination with 32 features. Finally 35 features for a single image are extracted. By applying Texture (GLCM) and RGB color feature extraction methods on surface image 35 features have been extracted. All the features extracted from above methods are used as an input to the BPNN classifier to classify the surface images based on their belongingness of the particular surface class.

V. EXPERIMENTATION

In this proposed methodology the wavelet and texture based features are used for six classes of surfaces to achieve higher rate of accuracy. The texture based features (GLCM) which are used to extract the surface features are Energy, Entropy, Contrast, and Homogeneity. During the training stage only 6x20=120 images are used. In order to calculate the performance of the proposed method totally 150 (6x25=150) surface images with varying co lor and design have been tested. Among 150 images, 143 images were correctly classified. The following confusion matrix table 5.1 illustrates the overall classification accuracy. The proposed system achieved average accuracy of classification 95.33% which has been calculated manually.

Table 5.1 Confusion Matrix for accuracy computation

	Class 1	Class2	Class3	Class4	Class5	Class6	Σ
Tile	**25**	0	0	0	0	0	25
Leather	1	**23**	0	1	0	0	25
Fabric	0	1	**24**	0	0	0	25
Metal	0	0	0	**23**	0	2	25
Plywood	0	0	0	0	**23**	2	25
Wood	0	0	0	0	0	**25**	25
Σ	26	24	24	24	23	29	**143**

The classification acuuracy is given by number of correctly classified images/Total number of testing images. Thus the classification accuracy is 95.33%. All the six classes such as Tile, Leather, Fabric, Metal, Plywood and wood are taken for study and the class wise classification accuracy is shown in table 5.2.

Table 5.2: Class wise classification accuracy

Class No.	Surface Classes	Accuracy
1.	Tile	100%
2.	Leather	92%
3.	Fabric	96%
4.	Metal	92%
5.	Plywood	92%
6	Wood	100%

VI. CONCLUSION AND FUTURE WORK

Texture is one of the precise concepts where each material surface deliberates different types of properties. The proposed system uses machine learning based surface material classification technique and it can be applicable in medical, photography, satellite and microscopic image processing fields. System overcomes some of the prep-processing issues and ensures that it can perform efficient and reliable classification. The system makes use of wavelet and texture based feature extraction methods to extract the features. The BPNN is employed as a classifier in order to produce expected results. The experiment is carried out on 6x25=150 surface images, where only 6x20=120 samples used for training purpose. Among 150 samples 143 samples are correctly classified. The proposed system achieved 95.33% classification accuracy. Future work of the project includes an analysis with more texture based features for surface materials and combined with present feature vector to obtain the higher accuracy.

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