Middle-East Journal of Scientific Research 23 (1): 59-65, 2015
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2015.23.01.22034

# An Efficient Feature Fusion Technique for Surface Grading of Ceramic Tiles

[1]M. Senthilkumar, [2]V. Palanisamy and [3]J. Jaya

[1]Department of Electronics and Communication Engineering, Anna University, Chennai, India
[2]Principal, Info Institute of Engineering, Coimbatore, Tamilnadu, India
[3]Principal, Akshaya college of Engineering & Technology, Coimbatore, Tamilnadu, India

**Abstract:** Automated grading system plays an important role in many industries. In ceramic industries, the grading of ceramic tiles is a difficult task as it has huge variations of surface properties. In this paper, automated surface grading system based on Discrete Wavelet Transform (DWT) and Gray Level Co-occurrence Matrices (GLCM) is presented. Texture information's in ceramic tiles are effectively represented by DWT at various decomposition levels. From the decomposition, DWT energy features are extracted. Also, the statistical features; correlation, contrast, energy, homogeneity are extracted from the GLCM of ceramic tiles. Feature fusion is employed for effective classification using Feed Forward Neural Network (FFNN) classifier. The evaluation of the system is carried on VxC TSG image database. Experimental results show that the proposed surface grading system produces 99.18% accuracy using $4^{th}$ level DWT features along with GLCM features

**Key words:** Surface grading · Gray level co-occurrence matrix · Wavelet transform · Nearest neighbor · Neural network.

## INTRODUCTION

Computerized surface grading of ceramic tiles become more importance for ceramic tile industry due to the vast development of infrastructure and the enormous utilization of ceramic tiles. To improve the grading system performance various researches have been carried out in the last decade and some of them are reviewed in this section. A new approach based on different neural network training is presented in [1] for automated marble classification. In order to classify the marbles, three types of feature extraction approaches; texture histograms, Discrete Cosine Transform (DCT) and DWT are used. Multilayer perceptron neural network is used for marble classification.

An automated granite tile classification system is implemented based on color texture analysis [2]. The colour descriptor approaches; co-occurrence matrices along with chromatic features, co-occurrence matrices along with colour percentile, Gabor features along with chromatic features, local binary patterns (LBP) and integrative co-occurrence matrices are employed. Various types of classifiers such as nearest neighbor, nearest mean neighbor, linear classifier, naive base classifier and Support Vector Machine (SVM) classifier are employed for granite tile classification.

A new method of color segmentation based marble tile classification system is designed in [3]. At first, the given colour image is transformed into HSI color space. Then, histogram based segmentation algorithm is employed for each band of HSI image. To locate the lobes of the histogram, the minima of the histograms are computed. Then, the segments are located by applying 8-neighbourhood region growing algorithm on the lobes. Finally, marble tile is classified by using distance measure.

Quality based automated marble classification is employed in [4]. Texture features based on Sum and Difference Histogram (SDH) is taken into account for feature extraction and four types of color spaces such as RGB, XYZ, YIQ and K-L are considered. SDH is nothing but an alternative of co-occurrence matrices, but with the advantages of decreasing computation time and memory storage. From the SDH, mean, energy, entropy, contrast, variance, correlation and homogeneity are obtained. The extracted features undergo dimension reduction by Principal Component Analysis (PCA). Then neural network classifier is applied for marble classification by training it with the extracted features.

**Corresponding Author:** M. Senthilkumar, Department of Electronics and Communication Engineering, Anna University, Chennai, India.

Image processing based marble quality classification system is reviewed in [5]. Several image analysis approaches such as darkening, lightening, cropping, reduction, zoom and resizing along with several methods such as, stretching, histogram calculation, thresholding and equalization is applied to the images for marble quality classification. The approaches are tested on gray color space and different color spaces like HSL, HSI, XYZ and CMY. Three types of scale spaces based marble quality classification is described in [6]. They are SDH, parametric texture model based on statistics of wavelets coefficients and blob model catches. The extracted features are classified with a common learning vector quantization network classifier.

Colour spectrum data based granite variety classification system is presented in [7]. The colour of granite varieties is characterized by using a colour reflectance measurement instrument. Spectrophotometer sensors are employed for image capturing and the captured reflectance data is transformed into spectral curve by employing smoothing process. The extracted spectral information is fed into SVM classifier for classification. Colour texture feature based surface grading system is implemented in [8]. Various color representation approaches such as CIE Lab, CIE Luv, RGB and grayscale are employed. Color texture descriptor such as mean, standard deviation and histogram moments from $2^{nd}$ to $5^{th}$ are extracted as features. KNN classifier is used for surface grading.

Gaussian multi scale representation based surface grading system is described in [9] for bamboo strips. Multivariate image analysis is used to extract the features. KNN classifier is used for surface grading along with Bhattacharyya distance. Hierarchical scheme based marble classification for surface images is introduced in [10]. SDH algorithm is used for feature extraction, where seven statistical features such as mean, variance, energy, correlation, entropy, contrast and homogeneity are computed. Various Adaboost algorithms are employed together to construct hierarchical classifier structure for marble classification.

Perceptual color grading system is implemented for ceramic tile images in [11]. At first, preprocessing takes place to restore the spatially blurred data using Wiener filtering. The restored data is transformed into CIE *XYZ* space and opponent colours space. From the converted color space, histogram features are exploited for ceramic tile grading system by using $x^2$ test. A new approach based marble surface image classification is introduced in [12] by using visual quality parameters. In order to classify the marble quality, multiresolution wavelet decomposition is analyzed and three marble categories are classified according with quality. Visual appearance of the granite tile image is analyzed in [13]. Texture features are extracted from the intensity plane along with pure chrominance features. The extracted coordinated clusters representation is used for granite tile classification.

In this paper, an automatic surface grading system for ceramic tile images based on DWT, GLCM and FFNN classifier is presented. The rest of this paper is organized as follows: The methodologies and the proposed surface grading system are described in sections 2 and 3 respectively. Section 4 gives the overview of VxC TSG image database. The experimental result of the proposed system is discussed in section 5. Finally, conclusion is made in the last section.

## MATERIALS AN DMETHODS

The proposed ceramic tile surface grading system is built based on DWT, GLCM and KNN classifier. The mathematical preliminaries of the aforementioned techniques are discussed in this section.

**Discrete Wavelet Transform:** Nowadays, wavelets are frequently used in signal/image processing to represent them at various resolution levels. The main applications of DWT are image compression, denoising, recognition and as well as in feature extraction. The 2D DWT decomposition is easily obtained by applying the 1D DWT to the rows first and then columns of the data. For 1-level decomposition, the number of sub-bands obtained by DWT is 4. Among the sub-bands, there are one low frequency sub-bands called LL band and three high frequency sub-bands called LH, HL and HH sub-bands. In general, further decomposition is applied only to the LL band. Figure 1 shows the multi resolution representation of gray ceramic tile image using DWT.

**Gray Level Co Occurrence Matrix:** The gray level co-occurrence matrix is a common technique in statistical image analysis that is used to estimate image properties related to second order statistics. GLCM considers the relation between two neighboring pixels in one offset, as the second order texture, where the first pixel is called reference and the second one the neighbor pixel.

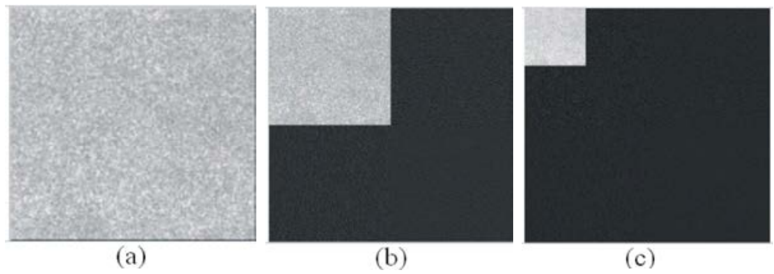

Fig. 1: DWT decomposition
(a) input image (b) 1-level decomposition (c) 2-level decomposition

GLCM is the two dimensional matrix of joint probabilities $p_{d,\theta}(i, j)$ between pairs of pixels. The use of co-occurrence probabilities using GLCM for extracting various texture features is explained in [14]. GLCM is also called as Gray level Dependency Matrix. It is defined as "A two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship."

**Correlation:** Correlation is a measure of gray level linear dependence between the pixels at the specified positions relative to each other.

$$Correlation = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\frac{\{i\times j\}\times p_{d,\theta}\{i,j\}-\{\mu_x\times\mu_y\}}{\sigma_x\times\sigma_y} \quad (1)$$

where, $\mu_x$, $\mu_y$, $\sigma_x$ and $\sigma_y$ are the means and standard deviations of $p_{d,\theta}$

**Contrast:** Contrast is a measure of intensity or gray level variations between the reference pixel and its neighbor. In the visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view.

$$\text{Contrast} = \sum_{n=0}^{N_g-1} n^2\left\{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)\right\}, \quad where\ n=|i-j| \quad (2)$$

when $i$ and $j$ are equal, the cell is on the diagonal and $i - j = 0$. These values represent pixels entirely similar to their neighbor, so they are given a weight of 0. If $i$ and $j$ differ by 1, there is a small contrast and the weight is 1. If $i$ and $j$ differ by 2, the contrast is increasing and the weight is 4. The weights continue to increase exponentially as $(i - j)$ increases.

**Energy:** Textural uniformity is computed by energy measure and it is also called Angular Second Moment (ASM). If an image is completely homogeneous, its energy will be maximum.

$$\text{Energy} = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} {p_{d,\theta(i,j)}}^2 \quad (3)$$

**Homogeneity:** Homogeneity is the measure of local homogeneity of an image and it also named as Inverse Difference Moment (IDM). IDM feature obtains the measures of the closeness of the distribution of the GLCM elements to the GLCM diagonal

$$\text{Homogeneity} = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}\frac{1}{1+(i-j)^2}p_{d,\theta(i,j)} \quad (4)$$

**Artificial Neural Network:** Artificial Neural Network (ANN) is a massively parallel distributed processing system made up of highly interconnected neural computing elements that have the ability to learn and thereby acquire knowledge and make it available for use. Various learning mechanisms exist to enable the ANN to acquire knowledge. ANN architectures have been classified into various types based on their learning mechanisms and other features. This learning process is referred as training and the ability to solve a problem using the knowledge acquired as inference [15].

**Properties of Neural Networks:**

- ANN has display mapping capabilities: Hence it can map input patterns to their associated output patterns.
- ANN learns by examples: Thus, ANN architectures can be trained with known examples of a problem before they are tested for their inference capability on unknown instances of the problem. They can, therefore, identify new objects previously untrained.
- ANNs possess the ability to generalize: Thus, they can predict new outcomes from the past trends and it process information in parallel, at high speed and in a distributed manner.

**Multilayer Feed Forward Neural Network:** The multilayered FFNN is made up with multiple layers. It possesses an input and an output layer and also has one or more intermediary layers called hidden layers. The computational units of the hidden layer are known as the hidden neurons or hidden units. The hidden layer aids in performing useful intermediary computations before directing the input to the output layer. The input layer neurons are linked to the hidden layer neurons and the weights on these links are referred to as input hidden layer weights. Similarly, the hidden layer neurons are linked to the output layer neurons and the corresponding weights are referred to as hidden output layer weights.

The forward calculation of a strictly 2-layer network with one output-node, i.e. network with one direct input-layer, one hidden-layer and one output layer consisting a single node is as follows [16] (i.e. network with $(N_i - N_j - 1)$ structure):

$$y(X,w)=\left[\sum_{j=0}^{N_j} g\left(\sum_{i=0}^{N_i} w_{ji}^{h} x_i\right) w_{kj}^{0}\right], \qquad g(z_0^h)=g(w_{oi}^h x_i)=1, x_0=1, k=1 \tag{5}$$

where $X = \{x_i,\ i=1,2,...,N_i\}$ denotes the network input vector and $w=\{\left[w_{kj}^{o}\right]_{j=0,...N_j:k=1}, [w_{ji}^{h}]_{i=0,...N_i:j=1,....,N_j}\}$ denotes the weight parameters to be adjusted. Sigmoidal function $g(.)$ is given by following eqn.

$$g(.) = \frac{1}{1+e^{-(.)}} \tag{6}$$

The superscripts '$o$' and '$h$' denotes weights that are connected to output nodes and hidden nodes respectively. For $n$ number of data points, input $X$ becomes an $n$-tuple vector (i.e. $X \in R^{(Ni+1)\times n}$ for $N_i$ number of input nodes plus a constant bias term) and so is the output $y$ (i.e. $y \in R^n$).

**Proposed Surface Grading System:** The two main important stages of the proposed surface grading system are feature extraction and validation. In feature extraction, the optimal features are extracted by exploiting DWT and GLCM techniques. The grade of the ceramic tiles is defined in the validation stage using FFNN classifier.

**Feature Extraction:** Feature extraction is one of the important phases of any classification system. Feature is a function of one or more image measurements that consists of quantifiable image characteristics. The design of the proposed feature extraction stage is shown in Figure 2.

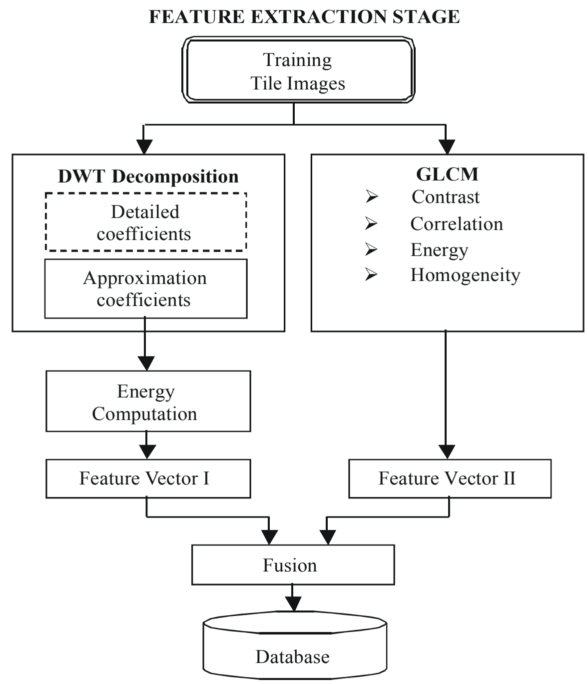


Fig. 2: Design of the proposed feature extraction process

To extract texture information's, the given training image undergoes 2D-DWT decomposition at predefined level. DWT iteratively transforms the original image into multiresolution subsets of approximate and detailed coefficients. In order to obtain descriptive feature, approximation coefficient alone taken into account as it is the approximation of original image. The energy of approximation coefficients is computed as feature vector. To consider the spatial arrangements of pixels in the image, statistical features such as contrast, correlation, energy and homogeneity is extracted from the GLCM of the given training image. Finally, the extracted DWT and GLCM features are combined to obtain optimal features. The procedure for feature extraction is repeated for all the training ceramic tile mages and extracted features are stored for further validation stage. As the VxC TSG database images are colour images, the proposed DWT and GLCM features are extracted for each channel individually and then combined to form the feature vector [16].

**Validation Stage:** Validation is the process of predicting group of the data instances. To simplify the problems of validation or classification, non parametric FFNN classifier is taken into account. It is robust and fault tolerant classifier. Figure 3 shows the block diagram of the validation stage of the proposed ceramic tile grading system.

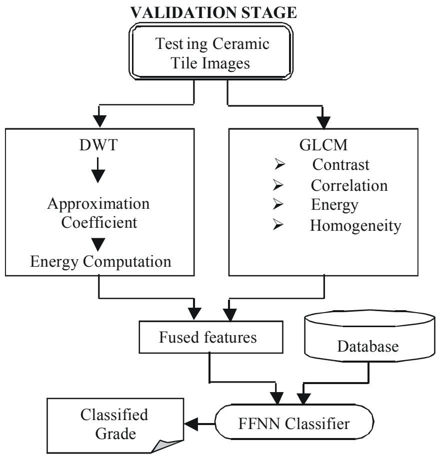


Fig. 3: Design of the proposed validation stage of surface grading system

To establish the surface grading system, DWT and GLCM features are extracted from testing ceramic tile images by using the same training image feature extraction procedure and fused. In order to predict the grade of the given test image, test features and stored feature database is fed to the FFNN classifier. The given features are passed from one layer to another and finally it reaches the output unit. To train the FFNN, back propagation algorithm is used. Finally, appropriate grade class is selected for the test image by the category associated with the output unit that has the largest output value. In this study, 25 hidden layers are used.

**VxC TSG Image Database:** In this study, all ceramic tile images in the VxC Tiles for Surface Grading (VxC TSG) database are used [17]. It has been created in association with Keraben S.A which is a prominent ceramic tile company, located at Province of Castellon. Hence the VxC TSG database samples are taken form ceramic industry, which is composed of 14 different ceramic models, 42 surface grades and 960 digital ceramic images. It comprised of three types of ceramic patterns such as fixed, random and pseudo random. The description of VxC TSG database is shown in Table 1.

Images are acquired through careful structuring of the lighting arrangement and camera position to improve features of interest such as limpidness and surface texture. Generally an optical system gathers an image, which is converted to a digital format and placed into computer memory. VxC TSG database is an extensive image database of ceramic tile that representing the wide range of surface classes in the ceramic tile industry. Figure 4 shows three different surface grades of ceramic tile models of Santiago, Oslo and mediterranea.

Table 1: Description of VxC TSG database

| Name | Classes | Tiles/Class | Size(cm) | Pattern | Aspect |
|---|---|---|---|---|---|
| Agata | 13,37,38 | 16 | 33x33 | Fixed | Marble |
| Antique | 4,5,8 | 14 | 23x33 | Pseudorandom | Stone |
| Berlin | 2,3,11 | 24 | 20x20 | Random | Granite |
| Campinya | 8,9,25 | 30 | 20x20 | Pseudorandom | Stone |
| Firenze | 9,14,16 | 20 | 20x25 | Random | Stone |
| Lima | 1,4,17 | 24 | 20x20 | Random | Granite |
| Marfil | 27,32,33 | 14 | 23x33 | Pseudorandom | Marble |
| Mediterranea | 1,2,7 | 30 | 20x20 | Random | Stone |
| Oslo | 2,3,7 | 24 | 20x20 | Random | Granite |
| Petra | 7,9,10 | 28 | 16x16 | Random | Stone |
| Santiago | 22,24,25 | 28 | 19X19 | Random | Stone |
| Somport | 34,35,38 | 28 | 19x19 | Random | Stone |
| Vega | 30,31,37 | 20 | 20x25 | Fixed | Marble |
| Venice | 12,17,18 | 20 | 20x25 | Pseudorandom | Marble |


Fig. 4: Different surface grades of Santiago, Oslo and mediterranea models
(a) Grade 1 (b) Grade 2 (c) Grade 3

## RESULT AND DISCUSSION

To evaluate the performance of the proposed ceramic tile grading system, the sample images in each ceramic model class are partitioned into two parts equally. One part is used for training the classifier and another part is used as testing set. The classification accuracy of the proposed FFNN classifier based surface grading system is compared with KNN based classifier. The DWT features are extracted at different levels and fused with GLCM features. Table 2 depicts the result of the proposed surface grading system using FFNN and KNN classifier.

Table 2: Average classification accuracy of the proposed system

| | FFNN | | | | KNN | | | |
|---|---|---|---|---|---|---|---|---|
| | Classification Accuracy (%) | | | | Classification Accuracy (%) | | | |
| Level | Grade1 | Grade2 | Grade3 | Avg | Grade1 | Grade2 | Grade3 | Avg |
| 1 | 87.48 | 95.51 | 95.75 | 92.91 | 97.55 | 98.98 | 98.47 | 98.33 |
| 2 | 94.42 | 90.56 | 95.78 | 93.59 | 97.55 | 98.98 | 98.47 | 98.33 |
| 3 | 93.83 | 95.99 | 97.96 | 95.92 | 97.55 | 98.98 | 98.47 | 98.33 |
| 4 | 99.49 | 100.00 | 97.96 | 99.15 | 97.55 | 98.98 | 98.47 | 98.33 |

Table 3: Classification accuracy of the proposed system at $4^{th}$ level of DWT decomposition

| | FFNN | | | | KNN | | | |
|---|---|---|---|---|---|---|---|---|
| | Classification Accuracy (%) | | | | Classification Accuracy (%) | | | |
| Database | Grade1 | Grade2 | Grade3 | Avg. | Grade1 | Grade2 | Grade3 | Avg. |
| Agata | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Antique | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Berlin | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Campinya | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Firenze | 100 | 100 | 100 | 100 | 90 | 100 | 100 | 96.67 |
| Lima | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Marfil | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Mediterranea | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Oslo | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Petra | 92.86 | 100 | 71.43 | 88.10 | 85.71 | 85.71 | 78.57 | 83.33 |
| Santiago | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Somport | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Vega | 100 | 100 | 100 | 100 | 90 | 100 | 100 | 96.67 |
| Venice | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

It is evident from the Table 2 that the proposed grading system achieves 99.15% accuracy using FFNN classifier at $4^{th}$ level decomposition. KNN classifier based grading system produces only 98.33% accuracy which is 0.82% lesser than FFNN classifier performances. The performance of KNN classifier is not affected by DWT features of various levels. Also, it is inferred that the classification accuracy of the proposed system increases while increasing the level of DWT decomposition. Table 3 shows the classification accuracy of the proposed system at $4^{th}$ level decomposition results.

It is observed form the Table 3 that Petra ceramic model alone misclassified in the proposed system using FFNN classifier. The average classification accuracy of Petra mode l is only 88.10%. While using KNN classifier, Firenze and Vega are also misclassified.

## CONCLUSION

An automated classification system for surface grading of ceramic tile images through computer vision is presented in this paper. To construct the proposed surface grading system, DWT and GLCM based features are taken into account for feature extraction whereas FFNN classifier is employed for surface grade classification. FFNN classifier is able to correctly predict the grade of ceramic tile images with 99.15% classification accuracy. The results show that the proposed surface grading system using FFNN classifier is highly effective and outperforms nearest neighbor classifier.

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