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# Granite Classification: An Industrial Application to Color Texture Classification

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***Abstract***— Color texture classification is a vital step for describing objects in natural scenes. A novel method is proposed to construct a histogram based on intensity and color channel neighborhood for the color texture classification. The goal of this paper is to explore the suitability of the histogram constructed using the intensity and color channel neighborhood relationship method in automatic classification of granite textures as an industrial application. Experimental tests are conducted on the images from VisTex database. Texture classification is performed using K-Nearest Neighbor (K-NN) and Support Vector Machine (SVM) classification methods. The average classification accuracy 97.93% is obtained for K-NN classification method, where as 100% average classification accuracy is achieved for SVM classification method. Further, experimentations are performed on MondialMarmi database of granite tiles to prove the potential of the proposed method in an industrial application. The classification results demonstrate that proposed method has improved classification accuracy as compared to other color texture classification methods. The results prove that proposed method using SVM is a powerful classification method for classifying granite textures.

***Keywords***—Color texture classification, Granite classification, Industrial application, Histogram features, Classification methods

## I. INTRODUCTION

Texture analysis plays a crucial role for solving problems such as segmentation, classification and pattern recognition in various computer vision tasks. Nowadays color texture classification methods are successfully used in numerous domains of machine vision like industrial application, medicine, content based image retrieval (CBIR), and face recognition among others [1, 2]. Color texture classification is considered a significant aspect in the industrial applications especially in automatic classification referred as 'grading' of products using their visual appearance. In past few years, many grading of industrial products such as paper [3], ceramic tiles [4] and fabric [5] have developed. Granite and wood are also considered as industrial products in the development of automatic machine vision system for grading. Automatic grading procedure is employed to overcome the issues like time-consuming, tedious and subjective by using manual quality control procedures.

Many researchers have developed different color texture classification methods. Paschos and Petrou [6], have invented histogram ratio features method to obtain improved results than the histogram intersection method for color texture classification. Porebski, Vandenbroucke and Macaire [7] implemented an approach for color texture classification by using haralic features extracted from co-occurrence matrices computed from Local Binary Pattern (LBP) images. The extension of the LBP method to three dimensional LBP method is introduced in [8], which produces three new color images for encoding both color and texture information of an image using the different color channels. Palm [9], has described three different approaches namely, sequential, parallel and integrative for classifying color texture images. Authors in [10], have employed a sequential approach based on histogram clustering from indexed images by combining classifiers for color texture classification. Chindaro, Sirlantzis and Deravi [11], have presented a multi-classifier method by the fusion of color space information using Gaussian markov fields. Support Vector Machine (SVM) classifier is used by authors for the color texture classification in [12]. Cusano, Napoletano, Schettini [13] have introduced a new method for color texture classification and also investigated the effects of varying light conditions on texture features using color normalization. In [14], authors have investigated that normalization and color spaces using parallel approach for color texture classification. In this work, a histogram constructed using the intensity and color channel neighborhood relationships. Five features namely, mean, standard deviation, homogeneity, slope and entropy are computed using the histogram bin values. Experimental tests are conducted on the images from VisTex database.

 

Texture classification is performed using classification methods such as K-Nearest Neighbor (K-NN) and Support Vector Machine (SVM). The proposed method yields 100% average classification accuracy for polynomial kernel function and resubstitution cross validation technique when SVM classification method is used. Further, experimentations are performed on MondialMarmi database of granite tiles to prove the potential of the proposed method in an industrial application. The classification results demonstrate that proposed method has improved classification accuracy as compared to other color texture classification methods. The results prove that proposed method using SVM is the most suitable for classifying granite textures.

The remainder of the paper is organized as follows: section II describes the proposed method, histogram construction and feature computations for the color texture image. In section III, color texture classification methods namely K-NN and SVM are explained. Experiments and results are demonstrated along with the application of granite classification using proposed method in section IV. The conclusion is drawn in section V.

## II. PROPOSED METHOD

The proposed method is divided into two parts, histogram construction and feature computations.

### A. *Histogram construction based on intensity and color channel information*

The histogram (H) is constructed using the intensity and color channels of a color texture image. We consider the pair of images for instance (I, R), where I is the intensity image and R is the red channel image and construct the histogram. It captures intensity variations as a texture along with color variations as described in [15], the detailed algorithm is presented in Appendix I. The histogram bin values are further used for the computations of features.

### B. *Feature computations*

The five features namely, mean, standard deviation, homogeneity, slope and entropy are computed using the histogram bins. The computations of features are as follows:

i. $$mean = \sum_{b=1}^{n} \frac{h_b}{n} \quad (1)$$

ii. $$stddev = \frac{\sqrt{\sum_{b=1}^{n} \left(h_b - mean\right)^2}}{n-1} \quad (2)$$

iii. $$\text{hom}\,ogeneity = \sum_{b=1}^{n} \frac{h_b}{b} \quad (3)$$

iv. *Slope* is computed from the regression line fitted across the normalized cumulative histogram of H (4)

v. $$entropy = -\sum_{b=1}^{n} h_b \left[\log_2\left(h_b\right)\right] \quad (5)$$

where n is the number of bins, $h_b$ is the height of $b^{th}$ bin of the histogram H. The methodology of the histogram construction and feature computation is illustrated diagrammatically in the Figure 1.

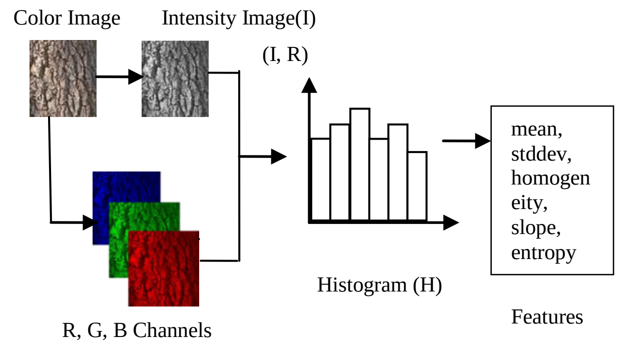


Figure 1. *Schematic diagram of the proposed method*

## III. COLOR TEXTURE CLASSIFICATION

Color texture classification has been carried out using different classification methods namely, K-Nearest Neighbor (K-NN) and Support Vector Machine (SVM).

### A. *K-Nearest Neighbor (K-NN)*

Classification of color texture images are performed in two stages, training and testing. The 50% of randomly selected samples from each class are used for training and remaining 50% samples are used for testing.

1) *Training:* The features are computed using the proposed method for each of the train samples and are stored in the feature library, which are further used for texture classification.
2) *Testing:* The features are computed using the proposed method for a test sample and compared with the features of all the training samples stored in the feature library using $l_1$-norm as the distance metric [16], given in (6),

$$D(p,q) = \sum_i \left|p_i - q_i\right| \quad (6)$$

where $p_i$ and $q_i$ are the feature vectors of training and testing samples respectively. Then the test sample is classified using K-Nearest Neighbor (K-NN) classification method. In the present work, it is chosen as K=1.

 

### *B. Support Vector Machine (SVM)*

The Support Vector Machine (SVM) classifies the data by choosing an optimal hyperplane that separates data points of one class from other classes. The best hyperplane for SVM is decided by the largest margin which is the maximum distance from decision surface to the support vectors [17]. Basically SVM is used for two-class classification in various tasks. Multiclass SVM can be divided into two types of approaches, one is one-against-one and other is one-against-all [18]. In this work, we have employed one-against-one approach for our multiclass problem. All tests are performed using kernel functions like Gaussian radial basis function (rbf), linear, polynomial, multilayer perceptron (mlp) for holdout, leavemout, kfold and resubstitution cross validation techniques. Experiments are performed with 10-fold cross validation, each fold with different number of training samples and testing samples for various kernel functions.

## IV. EXPERIMENTS AND RESULTS

To evaluate the classification results, experiments are carried out on VisTex database [19] of 164 images with dimension 128×128 pixels. For each texture class, an image is spilt into 20 overlapping sub-images with dimension 100×100 pixels which are randomly drawn. The 50% randomly chosen sub-images are used as training samples and the remaining 50% are considered as testing samples. Histograms are constructed for train and test samples by using the proposed algorithm. The features like mean, standard deviation, homogeneity, slope and entropy are computed by using histogram bins. The average classification accuracy is calculated over 10 experiments using K-NN and SVM classification methods.

The Table 1 presents the number of features and average classification accuracy obtained for different combinations of color channels along with intensity at distance d = 1 and angle $\theta = 0^{\circ}$ using K-NN classification method. The Table 2 shows the comparison of average classification accuracy for varying kernel functions and cross validation techniques of SVM classification method at distance d = 1 and angle $\theta = 0^{\circ}$ for (I, R), (I, G), (I, B) with 15 features. From the Table 1, it is observed that proposed method using K-NN classification method yields the optimal average classification accuracy of 97.93% for the combination of (I, R), (I, G), (I, B) with 15 features. Further, we have considered (I, R), (I, G), (I, B) combination with 15 features for SVM classification method. From Table 1 and Table 2, it is clear that SVM classification gives better results than the K-NN classification method. Table 2 indicates that, the proposed method yields 100% average classification accuracy for polynomial kernel function and resubstitution cross validation technique. It is also observed that, holdout cross validation technique achieves average classification accuracies 90.05%, 99.30%, 98.40%, 91.91% for rbf, linear, polynomial, mlp kernel functions respectively. The classification time for different kernel functions and holdout cross validation technique are 70.27s (rbf), 91.84s (linear), 120.03s (polynomial) and 97.92s (mlp) respectively.

Table 1. Average classification accuracy (%) of the proposed method using K-NN classification method at distance d=1 and angle $\theta = 0^{\circ}$.

| Intensity and color channel combination | No. of features | Average classification accuracy (%) |
|---|---|---|
| (I, R) | 5 | 93.55 |
| (I, G) | 5 | 93.17 |
| (I, B) | 5 | 91.04 |
| (I, R), (I, G) | 10 | 97.39 |
| (I, R), (I, B) | 10 | 97.08 |
| (I, G), (I, B) | 10 | 95.83 |
| (I, R), (I, G), (I, B) | 15 | 97.93 |

Table 2. Average classification accuracy (%) of the proposed method using SVM classification method for ((I,R),(I,G),(I,B)) with 15 features at distance d=1 and angle $\theta = 0^{\circ}$.

| Sr.no | Cross validation techniques | Kernel functions | | | |
|---|---|---|---|---|---|
| | | ***rbf*** | ***linear*** | ***polynomial*** | ***mlp*** |
| 1. | HoldOut | 90.05 | 99.30 | 98.40 | 91.91 |
| 2. | LeaveMOut | 94.27 | 99.51 | 99.09 | 91.22 |
| 3. | Kfold | 94.24 | 99.63 | 99.24 | 91.28 |
| 4. | Resubstitution | 99.79 | 99.91 | 100.00 | 91.98 |

It is found that rbf and linear computations take less amount of time compared to other two. Further, rbf and linear kernel functions with 15 features are considered for the industry based application namely, granite classification to show the effectiveness of the proposed method.

### *A. Application to granite classification*

Granite industry is in need of automatic classification method for granite tiles by sorting or grading of a product based on similar visual appearance. Granite is widely used material in façade cladding and pavement covering tasks because of its features like beauty, strength and lower price. In the market variety of granite tiles are available with different colors and textures. For this reason, we have chosen the automatic classification problem called grading in industry based application i.e. classification of granite tiles, to assess the suitability of the proposed method.

Many authors [20-22], have implemented automatic classification of granite textures to overcome the difficulties like costly shipping charges, late delivery, visually similar granite tiles caused by manual inspection method. A number of methods for automatic classification of granite textures have been proposed in recent years by many researchers [23-25]. In this paper, we have considered the granite textures data as given in paper [21]. MondialMarmi database [26] of granite tiles is freely available online. It contains 12 classes; each class consists of four tiles. For each class, an image is divided into 16 non-overlapping sub-images. This means each class constitutes 64 samples. Classification is carried out in two steps, one is training and other is testing.

Initially, experiments are evaluated on granite tiles using the proposed method by considering the hold out technique for ½ and 1-NN classification method with $l_1$-norm distance metric. It can be seen from the Table 3 that the proposed method yields higher average classification accuracy of 91.95% when compared to other state-of-the-art methods [23]. In Table 4 shown that the results of proposed method using K-NN have been enhanced by using SVM classification method.

Table 3. Results of granite classification yielded by the proposed method and other texture analysis methods using 1-NN classification method for (holdout, 0.5).

| **Texture analysis methods** | **Average classification accuracy (%)** |
|---|---|
| 3DLBP | 85.53 |
| CLBP_M | 82.30 |
| ILTP | 91.19 |
| IBGC1 | 85.34 |
| Proposed method | 91.95 |

Table 4. Results of granite classification using the proposed method for different classification methods

| **Training samples/total samples** | **Training type** | **Classification methods** | | |
|---|---|---|---|---|
| | | ***K-NN (%)*** | ***Linear SVM (%)*** | ***Rbf SVM (%)*** |
| 1/8 | Holdout, 0.875 | 88.54 | 91.84 | 90.41 |
| 1/4 | Holdout, 0.75 | 91.27 | 93.79 | 93.83 |
| 1/2 | Holdout, 0.5 | 91.95 | 94.89 | 95.52 |
| 3/4 | Holdout, 0.25 | 94.11 | 95.17 | 96.07 |
| 7/8 | Holdout, 0.125 | 93.85 | 95.47 | 96.50 |

The comparisons of average classification accuracy (%) of the proposed method using K-NN and SVM classification methods for (I, R), (I. G), (I, B) with 15 features at distance d = 1 and angle $\theta = 0^{\circ}$ are shown in the Table 4. From the Table 4, it is seen that for holdout, 0.5 the average classification accuracies obtained are 91.95%, 94.89% and 95.52% using K-NN, Linear SVM and Rbf SVM respectively. The Rbf SVM classification method yielded best results as compared to K-NN and linear SVM methods irrespective of any proportion of training samples. This shows that the proposed method using Rbf SVM yields better classification accuracy for granite classification.

## V. CONCLUSION

In this paper, a histogram is constructed using the intensity and a color channel neighborhood. Five features namely, mean, standard deviation, homogeneity, slope, entropy are computed using histogram bins and are used as color texture features. For texture classification K-NN and SVM classification methods are employed. The experimental results show that the proposed method yields 100% average classification accuracy when polynomial kernel function and resubstitution cross validation technique is used in SVM classification method. To prove the usefulness of the proposed method, it is used in an industrial application namely, granite classification. It is seen that the average classification accuracies obtained are 91.95%, 94.89% and 95.52% using K-NN, Linear SVM and Rbf SVM respectively. This study investigates that the proposed method gives better performance as compared to other color texture classification methods used for granite classification. The proposed method using SVM can be a suitable approach for automatic classification of granite tiles.

## APPENDIX I

The algorithm for histogram construction of a color texture image is described below:

1. Input the color texture image X= (R, G, B)
2. Compute I = 0.299*R + 0.587*G + 0.114*B
3. Histogram construction
   a. Consider the pair of images (I, R) as depicted in Figure 1.
   b. Consider a pixel $X_{ij}$ with its 8 neighbors in I and the corresponding pixel $Y_{ij}$ with its 8 neighbors in R as shown below:

| | | |
|---|---|---|
| $a_4$ | $a_3$ | $a_2$ |
| $a_5$ | $X_{ij}$ | $a_1$ |
| $a_6$ | $a_7$ | $a_8$ |

I

| | | |
|---|---|---|
| $b_4$ | $b_3$ | $b_2$ |
| $b_5$ | $Y_{ij}$ | $b_1$ |
| $b_6$ | $b_7$ | $b_8$ |

R

   c. Initialize the vector of b bins, H = 0;

```
for i = 1 to P
  for j = 1 to Q
 Let M=maximum(minimum(Xij, b1), minimum(Yij, a1));
          if M = = minimum(Xij, b1)
                 H(Xij) = H(Xij) + 1;
          end
    end
end
```

where P, Q is the size of the intensity image (I),
$X_{ij}$ is the $ij^{th}$ element in I,
$Y_{ij}$ is the $ij^{th}$ element in R,
$a_1$ is the neighbor of $X_{ij}$ at distance d = 1 and angle $\theta = 0^{\circ}$,
$b_1$ is the neighbor of $Y_{ij}$ at distance d = 1 and angle $\theta = 0^{\circ}$,
nb is the number of bins considered while histogram construction.

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