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Rock Textures Classification Based on Textural and Spectral Features

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***Abstract*—**In this paper, we proposed a method to classify each type of natural rock texture. Our goal is to classify 26 classes of rock textures. First, we extract five features of each class by using principle component analysis combining with the use of applied spatial frequency measurement. Next, the effective node number of neural network was tested. We used the most effective neural network in classification process. The results from this system yield quite high in recognition rate. It is shown that high recognition rate can be achieved in separation of 26 stone classes.

***Keywords*—**Texture classification, SFM, neural network, rock texture classification.

I. Introduction

TEXTURE is an important characteristic of many types of images in many application. The classification of stone texture is one of the most challenge classifications because the natural stones have quite various textures. Even they are in the same class, their textures are quite different.

Rock classification is quite demanding in industrial field because natural stone are widely used for decoration. The classification of natural stone textures is a difficult task. Rock texture in many cases is non-homogeneous which unlike most the Brodatz textures. Moreover, the granular size of the texture varies significantly in some rock types [2]. Generally, the classification of rock texture can be divided into textural and spectral features. There are former methods which extract the statistical features from textural intensity whereas some other considered about texture color [4].

Haralick et al firstly proposed the well known method, co-occurrence matrix features. However, 14 features are needed to compute. They are in different distances at different orientations. This process increases the computational and time complexity. Even if all the features was used, the correct classification rate can achieve at 60-70% [3]. The improvement in using co-occurrence matrix was later introduced [1]. The classification rate could reach up to 80% correct by focusing on only gray level of the images.

In addition to texture, color is also an essential feature to distinguish natural rock images. In our research study, we combined the textural features with the color information. Our proposed approach, we defined each type of natural rock images by using the combination of modified Spatial Frequency Measurement (SFM) and the values from eigenvector. The RGB images of rock were converted by the Principle Component Analysis (PCA) into the highest and the lowest eigenvalue bands. Three eigenvector values of the highest bands were used as color features and two modified SFM values were used as textural features. In recognition process, we used neural network to classify 26 classes of natural rock images. Our approach yielded promising results. This approach leads to an effective method for rock texture classification.

The paper was organized as following. In section 2, we described the overview of classification procedure and information preparations. Next, Spatial Frequency Measurement and its modified version were presented in section 3. Then, the results from features extraction and recognition processes were shown in section 4 and 5, respectively. Finally, in section 6, the conclusion will be provided.

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II. Classification Procedure

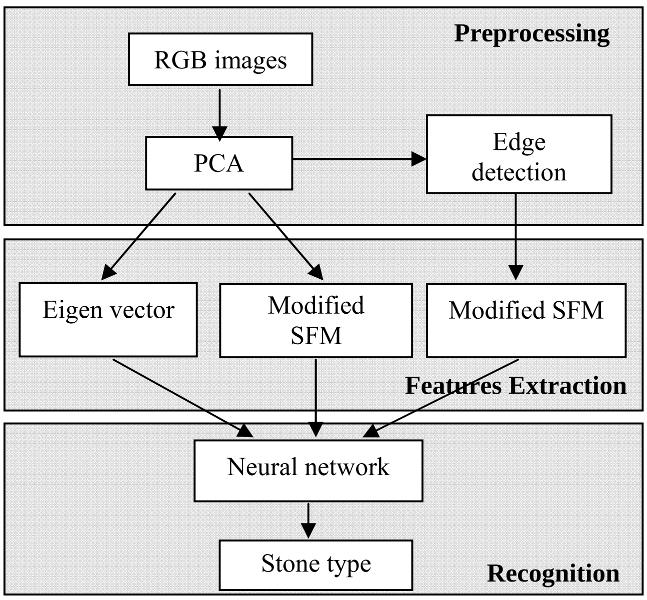


Fig. 1 An overview of classification procedure

Fig. 1 shows the classification procedure. Firstly, we reduced dimensions of data by PCA. In this process, PCA separates an image into three dimensions with different eigen values. Secondly, we selected the lowest and the highest eigen values to reconstruct two images. In addition, three values of eigenvector from the highest eivenvalue were used as features. highest eigenvalue band. Finally, 5 features from previous process were used in neural network to train and classify 26 classes of natural rock images.

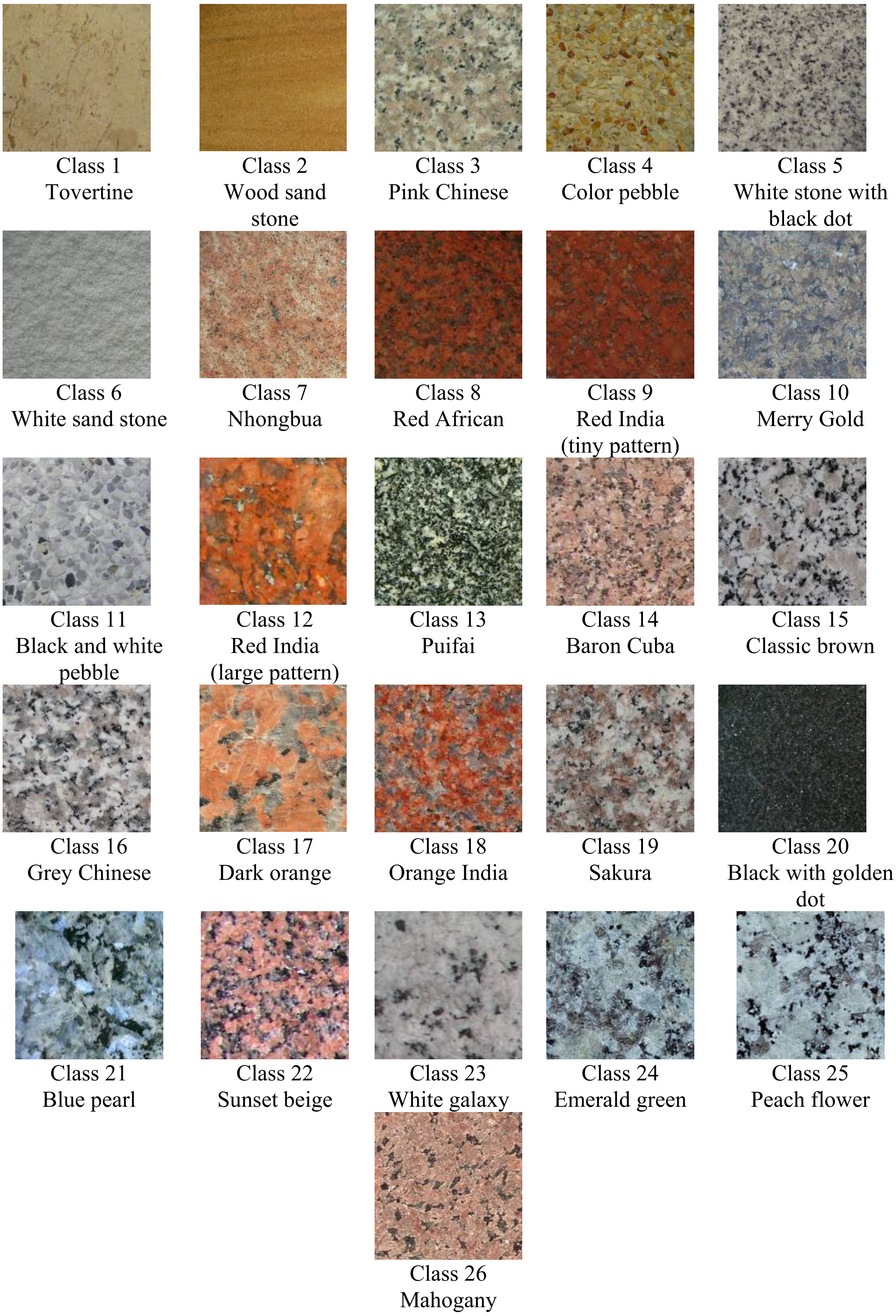


Fig. 2 Examples of 26 classes of natural rock texture images

Moreover, other features are extracted from applying the modified version of SFM on two images from PCA, an image from the lowest eigenvalue band and an edge image of the

A. Principle Component Analysis

Principle components analysis (PCA) is the way to clarify patterns of data, and expressing the data in such a way to highlight their similarities and differences. Moreover, applying PCA to color image can reduce the number of dimensions without much loss of information [5].When PCA is applied to RGB color images, it produces 3 × 3 covariant matrix size and three associated eigenvectors. If we take the eigenvector with the highest eigenvalue, we will get the principle component of the image. PCA can be performed as following:

$$A\bar{v} = \lambda\bar{v} \tag{1}$$

$$A - \lambda I = 0 \tag{2}$$

where A is a covariance matrix, λ is eigenvalue and $\bar{v}$ is eigenvector.

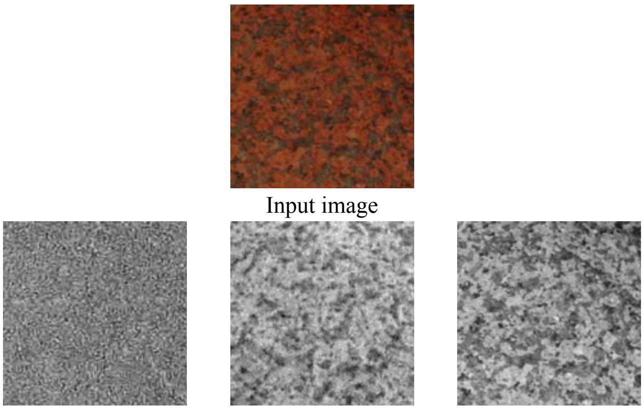


Fig. 3 Resulted images using PCA

From Fig. 3, the input RGB image was transformed into PCA images. PCA 1, PCA 2 and PCA 3 images was reconstructed from the lowest eigenvalue to the highest eigenvalue, respectively.

B. Sobel Edge Detection

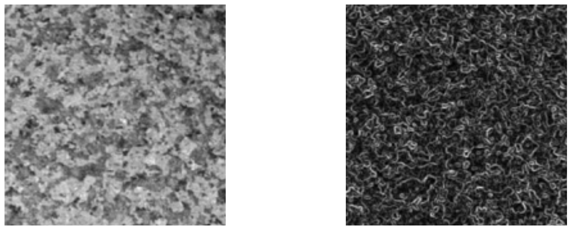
Edge detection is aimed to mark the points in a digital image at which the luminous intensity changes sharply. The change in properties of the image usually reflects the important events and information. Since, edge detection could used to isolate particular objects from their background, and to recognize or classify objects [6]. Therefore, we tested such edge detection operator and found out that Sobel operator was the most appropriate operator for our approach. They provided good edges and performed reasonably well in the presence of noise. Two masks, horizontal and vertical detectors of Sobel operator are shown as:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Where G_x is horizontal edge and G_y is vertical edge.

Therefore, the magnitude gradient of an image is obtained from;

$$G = \sqrt{G_x^{\,2} + G_y^{\,2}} \tag{3}$$



PCA 3 image　　　　Edge image

Fig. 4 Resulted images using Sobel edge operator

III. SPATIAL FREQUENCY MEASUREMENT (SFM)

SFM is used as a statistical textural feature to classify the rock textures because SFM indicates the overall activity level in an image. This can be defined as the characteristics of an image which can be evaluated in spatial domain [7]. SFM can be obtained from:

$$SFM = \sqrt{R^2 + C^2} \tag{4}$$

$$R = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=2}^{N}\left(x(m,n) - x(m,n-1)\right)^2} \tag{5}$$

$$C = \sqrt{\frac{1}{MN}\sum_{m=2}^{M}\sum_{n=1}^{N}\left(x(m,n) - x(m-1,n)\right)^2} \tag{6}$$

Where R is a row frequency and C is a column frequency, x(m,n) denotes the image.

M and N are quantity of pixels in horizontal and vertical direction, respectively.

Most statistical values depending on probability density functions cannot be used to classify the natural rock images because their probability density function of one type are quite similar to other types of rock. Hence, our proposed method, the modified version of SFM was used. According to SFM characteristic, the difference between the original image and the one-pixel shifted image was calculated from the original SFM equations. Then, we change the shifting distance from one pixel to *l* pixel(s). The modified version of SFM can be written as:

$$SFM_l = \sqrt{R_l^{\,2} + C_l^{\,2}} \tag{7}$$

$$R_l = \sqrt{\frac{1}{M(N-l-1)}\sum_{m=1}^{M}\sum_{n=1+l}^{N}\left(x(m,n) - x(m,n-l)\right)^2} \tag{8}$$

$$C_l = \sqrt{\frac{1}{(M-l-1)N}\sum_{m=1+l}^{M}\sum_{n=1}^{N}\left(x(m,n) - x(m-l,n)\right)^2} \tag{9}$$

And the modified textural feature of SFM can be calculated from:

$$\nabla SFM = \left|SFM_l - SFM_{l-1}\right| \tag{10}$$

From this equation, the modified version of SFM compares every *l* neighbor pixels. In our proposed approach, we selected *l* =2 so the result was different value between one pixel shifted image and two pixel shifted image.

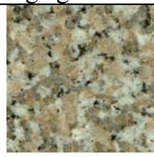
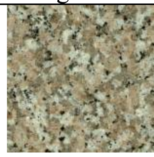
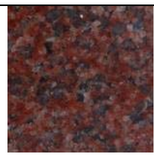
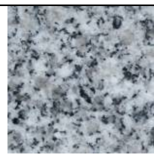
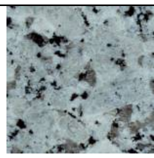
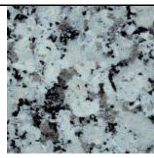
IV. Feature Extraction

From the modified version of SFM, the result graphs were plotted. The first graph was the results of modified SFM applying to the highest eigenvalue edge images. X-axis was modified SFM values and Y-axis was classes of stone.

The graph in Fig. 5 shows that the modified SFM can divide rock textures into two groups, homogeneous and non-homogeneous. The homogeneous group gets lower modified SFM values than the non-homogeneous group.

Moreover, the modified SFM value of the highest eigenvalue edge image can separate a large grain stone from a small grain stone in the same class. A large grain stone gets the lower values than a small grain stone. The results of these are shown in Table I:

TABLE I
THE MODIFIED SFM VALUE OF STONE IMAGE IN DIFFERENT GRAIN SIZE

Large grain stone	Small grain stone	Class No.
 SFM = 51.962	 SFM = 64.464	3
 SFM = 19.585	 SFM = 27.152	12 and 9
 SFM = 50.629	 SFM = 68.236	16
 SFM = 68.266	 SFM = 94.264	25

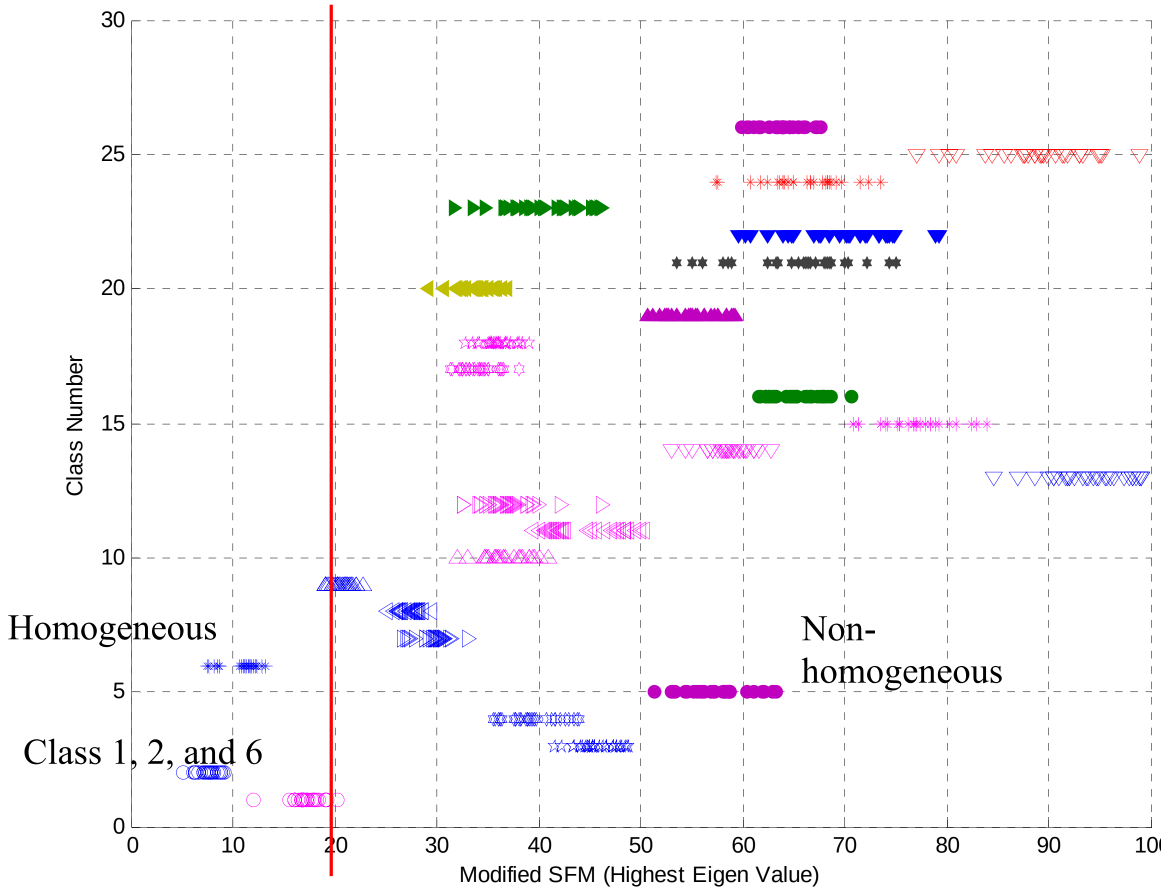


Fig. 5 A classification result after applying modified SFM to the highest eigenvalue edge images

The modified SFM values from the lowest eigenvalue images shown in Fig. 6 gives the different information from the modified SFM values of the highest eigenvalue edge images. These values can classify different groups from the modified SFM values of the highest edge images. So, this result could be use to support the classification process.

The graph in Fig. 7 is the combination between the modified SFM values from Fig. 5 and 6.

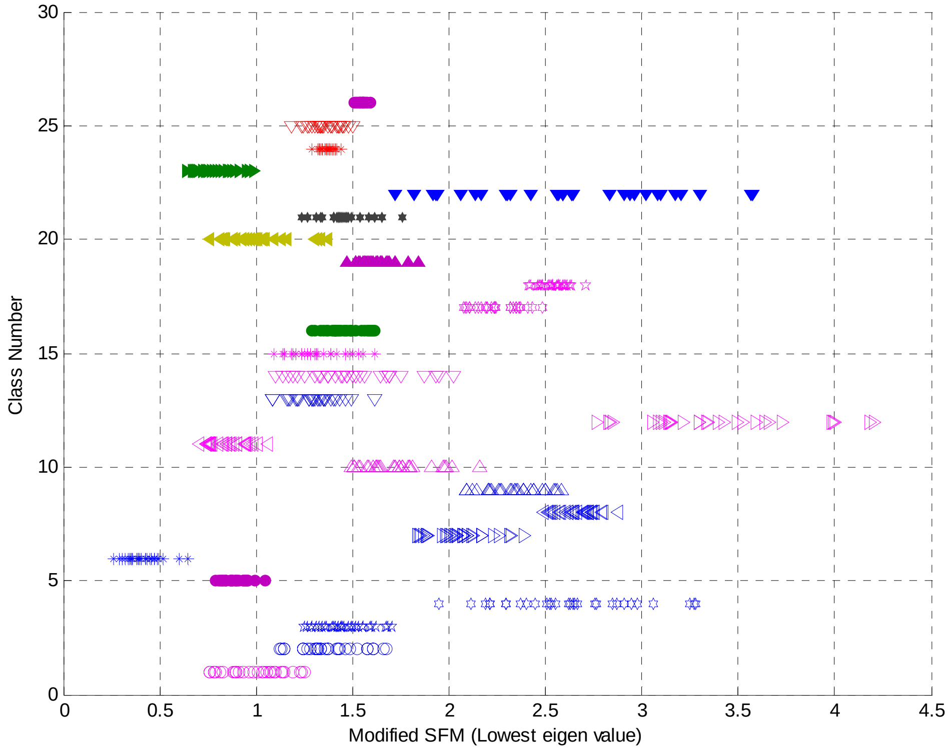


Fig. 6 A classification result after applying modified SFM to the lowest eigenvalue edge images

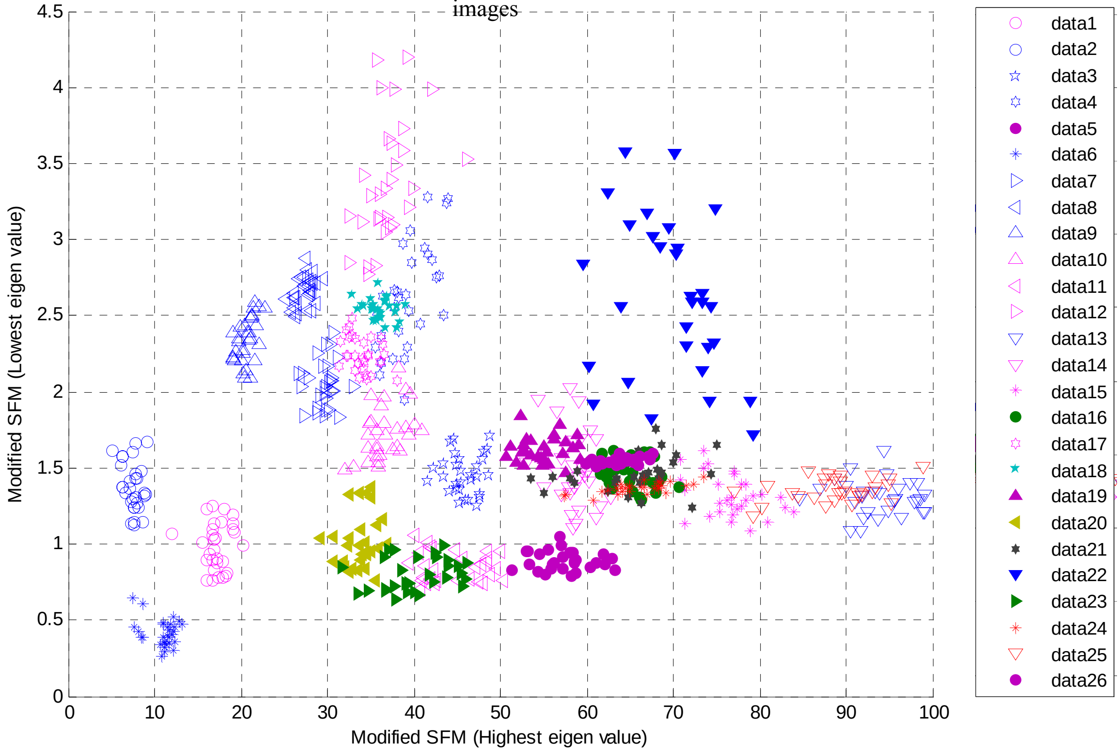


Fig. 7 A classification result after combining the modified SFM of the highest and lowest eigenvalue edge image results

The result shows that only the textural features of the modified SFM were not enough to classify 26 classes of rock texture because several classes stay in the same region. Therefore, the color features from the eigenvector of the highest eigenvalue will be needed to enhance the classification result.

V. Classification process

Since we used 30 images for each type of stone, we separated them into 2 groups, 10 images for a train group and 20 images for a test group. A train group was used for neural network training. After the training process completed, a test group will be used to evaluate the efficiency of a system.

We tested the appropriated hidden layer 1 and 2 nodes of neural network as following. In the Table II and III, we highlighted the most accurate recognition rate of hidden layer 1 and 2 nodes. Therefore, the most appropriate node numbers for hidden layer 1 and 2 are 12 and 18, respectively.

We create neural network contained 5 input nodes, 12 hidden nodes in level 1, 18 hidden nodes in level 2, and 26 output nodes. Input nodes are the five values obtained from the modified SFM of the highest eigenvalue edge image, the modified SFM of the lowest eigenvalue image, and three values from eigenvector of the highest eigenvalue. Output nodes of neural network were 26 classes of natural rock textures.

We evaluate a system by calculating the Fault Acceptance Rate and Fault Rejection Rate from the classification process. The result of this system is shown in Table IV.

TABLE II
Appropriated Hidden Layer 1 Nodes Experiment

Hidden nodes	RMS [a]	Correct elements	Recognition rate (%)
1	0.169455	131	29.04
2	0.144014	399	80.58
3	0.03651	479	95.96
4	0.0267	475	95.19
5	0.995086	486	97.31
6	0.01869	485	97.12
7	0.016476	488	97.69
8	0.014395	483	96.73
9	0.015622	485	97.12
10	0.015038	488	97.69
11	0.015448	487	97.5
12	0.011075	493	98.65
13	0.012979	492	98.46
14	0.01592	481	96.35
15	0.013455	488	97.69
16	0.013674	479	95.96
17	0.011937	486	97.31
18	0.012887	490	98.08
19	0.013398	492	98.46
20	0.012178	492	98.46

[a]RMS means root mean square error between training data and output.

From the results, neural network achieves a good result. Only 5 classes of natural rock texture images have some mistakes. The overall system shows the effective of using our proposed method to classify 26 classes of stone.

TABLE III
Appropriated Hidden Layer 2 Nodes Experiment

Hidden nodes	RMS	Correct elements	Recognition Rate (%)
1	0.19231	0	3.85
2	0.192309	5	4.81
3	0.192309	0	3.85
4	0.170899	134	29.62
5	0.103152	450	90.38
6	0.088401	452	90.77
7	0.103985	428	86.15
8	0.070866	462	92.69
9	0.042759	475	95.19
10	0.041444	468	93.85
11	0.028982	482	96.54
12	0.016521	486	97.31
13	0.021156	476	95.38
14	0.017275	490	98.08
15	0.017563	485	97.12
16	0.017147	483	96.73
17	0.015344	483	96.73
18	0.015812	491	98.27
19	0.016018	490	98.08
20	0.015283	477	95.58
21	0.014168	490	98.08
22	0.013874	485	97.12
23	0.011872	490	98.08
24	0.013212	486	97.31
25	0.011782	489	97.88
26	0.016089	486	97.31
27	0.013738	490	98.08

TABLE IV
Classification Result

Class	FAR [a]	FRR [b]	Class	FAR	FRR
1	0	0	14	0	25%
2	0	0	15	0	0
3	0	0	16	0	0
4	0	0	17	0	0
5	10%	0	18	0	0
6	0	0	19	0	0
7	0	0	20	0	0
8	0	0	21	0	0
9	0	0	22	0	0
10	0	0	23	0	0
11	0	0	24	10%	0
12	0	0	25	0	10%
13	0	10%	26	25%	0

[a]FAR means Fault Acceptance Rate
[b]FRR means Fault Rejection Rate

FAR, FRR and RMS can be computed as following equations:

$$\mathrm{FAR} = \frac{\#\ \text{Fault Accept Elements}}{\#\ \text{Elements in Class}} \times 100 \tag{11}$$

$$\mathrm{FRR} = \frac{\#\ \text{Fault Reject Elements}}{\#\ \text{Elements in Class}} \times 100 \tag{12}$$

$$\mathrm{RMS} = \frac{\sqrt{\sum\left(\text{output node} - \text{target data}\right)^2}}{\left(\#\text{output node} \times \#\text{pattern}\right)} \tag{13}$$

VI. Conclusion

In this paper, a combining both color and textural information method to classify each type of rock was proposed. The values from eigenvector and modified version of SFM were use as features to distinguish each class of natural rock texture images along with neural network. PCA transformation creates the different information from RGB image. This difference leads to effective preservation of both time and information. The modified SFM is used as the textural statistical features. When applying the modified SFM to the edge image from the highest eigenvalue band, we can classify rock into homogeneous and non-homogenous groups. While applying modified SFM to the lowest eigenvalue image, we get the distinct information, and this information is used to enhance the classification result. Importantly, the values from eigenvector support the color information of each rock type. The results from a simulation system are shown that our proposed approach yields promising results. It leads to an effective method for natural rock texture classification.

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