Image Classification Schemes Based on Gradient Matrix and Contrast Matrices

Hashim Abbas1* & Loay E. George2
1 Department of Optics Techniques, College of Health and Medical Technology, Al Ayen University, Iraq
2 Assistance of the University president for Scientific Affair, University of Information Technology & communication, Iraq

abbashashim88@gmail.com

Abstract

Texture classification and categorizing are used in various pattern recognition applications and classification texture that possesses a characteristic appearance. This work aims to provide an improved scheme of enhanced classification decision with the need to increase the precision time significantly. This research studied the discriminating characteristics of textures by extracting the feature from gradient matrix (GM), the features were extracted using the first-order gradient feature vector, three Gradient Matrices were established, one for Max value, another for Min value and last was the Average value, these matrices were calculated by extracting the gradient along x-axis and y-axis and the gradient along the diagonal. A feature vector consist of 210 features was calculated to represent each image sample and contrast matrix CM, The feature extracted from CM1 was The difference between the sum of the neighborhood values of 3x3 pixels those larger than the pixel values (center pixels) divided by their number and the sum of the neighborhoods values of 3x3 pixels those smaller than the pixel value divided by their number total feature vector was 210, Four types of Euclidean distance metrics were used for classification decision purposes. The concepts “average” and “standard deviation” were calculated to perform the inter-entra scatter analysis for each feature to find out the best discriminating features that can be used. The final result of the test set of GM is 98.3 while training set was 97.3, the final result of the test set of CM is 98.2 while training set was 95.7.

1.1 Introduction

Image texture is a huge field of research and is understood as a fundamental component in computer vision, this has opened the door wide to create new solutions too many problems that were considered unfeasible and computationally demanding [1]. Texture analysis is the operation of extracting important information from the surface of an object(s) showing an image, where this object could take a small region or the whole image. The texture is a significant property of digital images, the image texture does not have a formal description it can be regarded as a function of the variance of pixel intensities that form repeated patterns.
Assessing the performance criteria of the utilized feature extraction process requires choosing an appropriate classification algorithm or metric (dis)similarity measures [4], Matthew and et al. used invariant combinations of linear filters. Unlike previous methods, it introduce a novel family of filters, which provides scale invariance, resulting in a texture description invariant to local changes in orientation, contrast. A texture discrimination method based on the 2 similarity measure used to histograms derived from our filter responses outperforms existing methods for retrieval and recognition results for both the Brodatz textures and the University of Illinois [5]. Duda. Proposed the method to analyze simultaneously the triplets of prostate MR images, corresponding to the same prostate slice, but derived from different image series: the contrast-enhanced T1, the T2, and the diffusion-weighted one. Two classes of prostatic tissue were differentiated: tumorous and healthy, their ability of characterizing prostatic tissue was assessed using three classifiers: Logistic Regression (LR), Neural Network (NN) and SVM. The 10-fold cross validation was used to assess the classification accuracies. The best overall classification result exceeded 99% and corresponded to the application of the SVM classifier [6]. Patil and et al. tried to differentiate the four grades of Astrocytoma (from Grade I to Grade IV). Their approach consisted of several stages: image preprocessing, segmentation, feature extraction and classification. The involved Feature extraction used the co-occurrence technique for providing a set of 11 features. Finally, the PNN has been developed to differentiate between different grades of considered brain tumor. The overall accuracy of the system (obtained on the test set) was of 94.87% [7]

2.1 Gradient Matrix (GM)

The gradient at a particular point in an image is the rate of the variance between the gray levels of its adjacent pixels (i.e. neighboring pixels), either in the horizontal or vertical direction or diagonal direction as shown in figure (1). The gradient values are calculated by taking the discrete derivative (finite difference):

\[
G_x(x, y) = \frac{\partial V(x, y)}{\partial x} \approx V(x + 1, y) - V(x, y)
\]

(1)

\[
G_y(x, y) = \frac{\partial V(x, y)}{\partial y} \approx V(x, y + 1) - V(x, y)
\]

(2)

\[
G_D(x, y) = \nabla V(x, y) \approx V(x + 1, y + 1) - V(x, y)
\]

(3)

Therefore, the gradient points be in the direction of most rapid increase in intensity of pixel and its neighborhood. Often a neighborhood of 3 × 3 pixels is considered.

![Figure (1) Neighborhood Values of Pixels in GT](image)

The GM contains the values of the gradient at each point of an analyzed image region, excluding its boundaries. Lerski et al. introduced the GT-based features. After calculating the gradient values, two matrices of gradient were established [8]:

\[
Gradient_{\text{Min}} = \text{Min}(G_x, G_y, G_D)
\]

(4)
Minimum and maximum are Scale of similarity and contrast between the extracted features, Minimum distance is a measure of the similarity, maximum distance is the measure of contrast, when the Minimum value is small the features are similar otherwise, the measure of contrast is increases by increasing the value of the maximum

2.2 Contrast Matrices

Contrast is the variance in visual properties that makes an object (or its representation in an image) recognizable from other objects and the background. In visual perception of the real world, contrast is determined by the variance in the color and brightness of the object and other objects within the same field of view. In other words, it is the variance between the darker and the lighter pixel of the image, if it is big the image will have high contrast and in the otherwise the image will have low contrast [9]. Contrast can be simply explained as the evaluated for maximum or minimum intensity for the pixel in an image or the difference between the intensity of values surrounding (i.e. the neighborhood of pixel) to each pixel in the image. In this work three methods was used to compute the CM.

The first method CM was calculated as follows: The difference between the sum of the neighborhood values of 3x3 pixels which are larger than the pixel values (center pixels) see figure (2) divided by their number and the sum of the neighborhoods values of 3x3 pixels which are smaller than the pixel value divided by their number

\[
\text{Contrast_1} = \frac{\text{Sum}_{\text{big}}}{n_{\text{big}}} - \frac{\text{Sum}_{\text{small}}}{n_{\text{small}}} 
\]

Where

\[
\text{Sum}_{\text{big}} = \frac{\text{sum}(v) > v}{n_{\text{big}}} \quad , \quad \text{Sum}_{\text{small}} = \frac{\text{sum}(v) > v}{n_{\text{small}}}
\]

Then tack the absolute value of the contrast of equation (5)

Figure (2) Neighborhood Values of 3x3 Pixels in Gray Color

3. MATERIALS AND METHODS
3.1 Data Description

The applied examination methods for GM and CM features have been tested on various color images in 32 data sets. Three combinations of color images were used, each is a BMP with 256 gray levels, while the size of each image is 128x128 pixels. The sets are shown in Table- 1 below, with each set consisting of the different number of classes and 16 samples into each class. The used sets are loaded from Salzburg Texture Image Database (STex); it is a large collection of color texture images that have been captured around Salzburg, Austria. The images have been selected to be used in texture analysis experiments.

| Class      | Sub Class | Total image |
|------------|-----------|-------------|
| Porcelain   | 2         | 32          |
| Track       | 2         | 32          |
| Straw       | 3         | 48          |
| Tire        | 3         | 48          |
| Tree        | 3         | 48          |
| Grass       | 4         | 64          |
| Rattan      | 4         | 64          |
| Sponge      | 4         | 64          |
| Tiles       | 4         | 64          |
| Building    | 5         | 80          |
| Leaf        | 5         | 80          |
| Styrofoam   | 6         | 96          |
| Leather     | 7         | 112         |
| Plastic     | 8         | 128         |
| Food        | 10        | 160         |
| Paper       | 10        | 160         |

3.2 Methodology

- This section presents the performed steps and consists of the following stages as shown in figure (3):
- Prep-processing stage.
- Features vector extraction stage.
- Classification stage.
3.2.1 Prep-processing stage

The first stage as shown in figure (3) in any recognition system is preprocessing. In this stage, a sequence of image processing operations is utilized to make the image (that is loaded to the system as an input) appropriate for extracting the related information to obtain the best recognition results. In this research, the following pre-processing steps were applied: to read images and color decomposition as a first step, the loaded images were decomposed into three color bands (or channels). The basic color components are Red, Green, Blue, and these gray color values were evaluated. The second step divides the images into four sub-images, each sub-image has a size 64 × 64 pixels.

3.2.2 Features Extraction Stage

After performing the previous steps (reading the image, color decomposition, splitting) figure (3), the feature extraction stage was applied to extract some of the textural attributes. The aim of the feature extraction is to obtain a set of texture measures that can be used to distinguish among different texture pattern classes. In this paper, one of the most important texture analysis methods was used to extract a certain kind of feature vector by utilizing the GM and CM. From each sub-image, 210 features for each GM and CM were extracted. Also, some variants for this method are introduced to develop more efficient sets of discriminating features.

3.2.3 Features Analysis and Selection Stage

A training set of samples was applied to train the classifier and to address the feature list. While, the test set was applied to assess the recognition accuracy of the system (after the training phase). To obtain a robust recognition performance, this step is claimed to reduce the feature size.

Figure (3) Diagram illustrate the methodology of the work
and to choose the most related and discriminative features companion with the lowest intra-distance and highest inter-distance among the discriminations, then combining the best set of features that led to the best verification result [10].

### 3.2.4 Classification Stage

In this research, the classification of those attributes was complete due to their inter-class stability. Through the practicing phase, certain features were selected from the overall set of features; the selection was due to the comprehensive tests which were proceeded on the set of samples to find out the best features that can be utilized to yield highest matching results.

#### 3.2.4.1 Matching

The matching steps determine the match outcome (or in other words, the similarity measure) between the feature vectors extracted from the input samples and the stored templates. The similarity result should be high for samples categorized to the same class and least for those categorized to different classes. Sample matching is usually a difficult pattern recognition task due to large intra-class variations (i.e., variations in sample images for the equivalent class) and large inter-class similarity (i.e., the similarity between sample images from the altered class). In this paper, the features extracted in the preceding stage have been used to match either the tested samples data previously stored in the database (i.e., belong to training set) or other samples (i.e., testing set). To accomplish matching, the features of the samples that belong to the training set were used to yield the template mean feature vector for each class. The mean feature vector (F) of each class and the corresponding standard deviation vector (σ) were determined and saved in a dedicated database during the training phase. These parameters were used as template vectors. They were determined using the following equations [11]:

\[ F(c,f) = \frac{1}{s} \sum_{i=1}^{s} F(c,fi) \]

\[ D_2(\overline{T}_i, \overline{F}_i) = \sum_{k=1}^{m} \left( \frac{T_i(k) - f_j(k)}{\sigma_i(k)} \right)^2 \]

\[ D_3(\overline{T}_i, \overline{F}_i) = \sum_{k=1}^{m} \left( \frac{T_i(k) - f_j(k)}{\sigma_i(k)} \right) \]

\[ D_4(\overline{T}_i, \overline{F}_i) = \sum_{k=1}^{m} \left( \frac{T_i(k) - f_j(k)}{\sigma_i(k)} \right)^2 \]

Where \( T_i \) is the template (mean) of class i, and \( \sigma_i \) is the standard deviation of class i. In order to maximize the probability of the match classification and minimize misclassification rate. The efficiency of classification is calculated for each distance using the following equation [12]:

\[ \text{Efficiency} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{D_i} \]
\[ \eta(\%) = \frac{\text{Total no. of samples} - \text{No. of misclassified samples}}{\text{Total no. of samples}} \times 100\% \quad (9) \]

4. EXPERIMENT RESULTS

Each image vector has 210 features extracted for all images’ classes, using the GM method with filter size 3x3. Table (2) presented the GM result. Each table presents the result of how many features that used to perform the classification for example table (2) represents the accuracy rate of D1, D2, D3, and D4 of one feature some classes had 100% and the other improved by adding feature until the feature seven. Table (3) presents the final result of GM. However, our results show that: 9 classes have 100 scores, 23 classes have above 90 scores, the total result in both table 3, and 5 came from the average value from test sets and training sets. While CM result produced by a feature vector consists of 210 feature were extracted using CM with filter size 3x3. Table (4) present the result where a certain number of features were used to perform the classification. When combinations of more feature were used to reach the classification rate (100%) or till adding seven features table (4). Table (5) presents the final results of CM. However, the test results showed that: 10 classes have 100% of success rate score, 22 classes have above 90 scores.

Table (2): The Results of GM (Using Seven Features)

| No. Feature | Class   | No. of Sub Class | D1%  | D2%  | D3%  | D4%  |
|-------------|---------|------------------|------|------|------|------|
| 7           | Porcelain| 2                | 100  | 100  | 100  | 100  |
| 7           | Track   | 2                | 100  | 100  | 100  | 100  |
| 7           | Straw   | 3                | 100  | 100  | 100  | 100  |
| 7           | Tire    | 3                | 90.1 | 88.54| 92.18| 92.7 |
| 7           | Tree    | 3                | 98.95| 100  | 100  | 100  |
| 7           | Grass   | 4                | 92.57| 92.96| 94.53| 95.7 |
| 7           | Rattan  | 4                | 98.82| 95.31| 99.6 | 100  |
| 7           | Sponge  | 4                | 94.53| 94.92| 96.48|      |
| 7           | Tiles   | 4                | 100  | 100  | 100  | 100  |
| 7           | Building| 5                | 87.81| 87.18| 93.43| 95.31|
| 7           | Leaf    | 5                | 89.37| 90.62| 89.68| 90.31|
| 7           | Styrofoam| 6               | 99.73| 100  | 100  | 100  |
| 7           | Leather | 7                | 90.32| 91.4 | 92.96| 92.57|
| 7           | Plastic | 8                | 87.5 | 88.02| 91.66| 97.39|
| 7           | Food    | 10               | 92.81| 93.43| 95   | 95.31|
| 7           | Paper   | 10               | 96.4 | 97.34| 99.53| 100  |
| 7           | Floor   | 11               | 83.59| 83.59| 89.06| 90   |
| 7           | Rubber  | 11               | 98.75| 99.06| 99.34| 100  |
| 7           | Bark    | 13               | 91.4 | 92.44| 94.53| 95.57|
| 7           | Flower  | 13               | 93.75| 96.34| 96.35| 96.87|
| 7           | Marble  | 13               | 85.41| 86.97| 87.76| 93.22|
| 7           | Technic | 14               | 87.81| 87.81| 88.75| 90.62|
| 7           | Hair    | 15               | 88.12| 87.5 | 90   | 93.12|
| 7           | Paint   | 15               | 91.4 | 93.43| 95.78| 97.03|
Table 3: The Final Results of GM

| No. Feature | Class   | No. of Sub Class | Testing Data | Training data | Total Data |
|-------------|---------|------------------|--------------|---------------|------------|
| 7           | Porcelain | 2                | 100          | 100           | 100        |
| 7           | Track    | 2                | 100          | 100           | 100        |
| 7           | Straw    | 3                | 100          | 100           | 100        |
| 7           | Tire     | 3                | 96.04        | 92.7          | 94.37      |
| 7           | Tree     | 3                | 100          | 100           | 100        |
| 7           | Grass    | 4                | 98.35        | 95.7          | 97.025     |
| 7           | Rattan   | 4                | 100          | 100           | 100        |
| 7           | Sponge   | 4                | 99.08        | 96.35         | 97.78      |
| 7           | Tiles    | 4                | 100          | 100           | 100        |
| 7           | Building | 5                | 97.25        | 95.31         | 96.28      |
| 7           | Leaf     | 5                | 94.32        | 90.31         | 92.315     |
| 7           | Styrofoam| 6                | 100          | 100           | 100        |
| 7           | Leather  | 7                | 96.36        | 92.57         | 94.465     |
| 7           | Plastic  | 8                | 99.99        | 97.39         | 98.69      |
| 7           | Food     | 10               | 98.15        | 95.31         | 96.73      |
| 7           | Paper    | 10               | 100          | 100           | 100        |
| 7           | Floor    | 11               | 93.24        | 90            | 91.62      |
| 7           | Rubber   | 11               | 100          | 100           | 100        |
| 7           | Bark     | 13               | 98.92        | 95.57         | 97.245     |
| 7           | Flower   | 13               | 97.99        | 96.87         | 97.43      |
| 7           | Marble   | 13               | 97.54        | 93.22         | 95.38      |
| 7           | Technic  | 14               | 95.33        | 90.62         | 92.975     |
| 7           | Hair     | 15               | 96.05        | 93.12         | 94.585     |
| 7           | Paint    | 15               | 99.14        | 97.03         | 98.085     |
| 7           | Bush     | 18               | 98.58        | 93.59         | 96.085     |
| 7           | Gravel   | 20               | 99.16        | 96.4          | 97.78      |
| 7           | Stone    | 29               | 99.03        | 98.04         | 98.535     |
| 7           | Wall     | 30               | 96.74        | 93.75         | 95.245     |
| 7           | Metal    | 31               | 95.35        | 92.96         | 94.155     |
| 7           | Wood     | 41               | 100          | 99.68         | 99.84      |
| 7           | Misc     | 44               | 100          | 98.59         | 99.295     |
Table (4): The Final Results of CM_1 (for Seven Features)

| No. Feature | Class     | No. of Sub Class | D1%     | D2%     | D3%     | D4%     |
|-------------|-----------|------------------|---------|---------|---------|---------|
| 7           | Porcelain | 2                | 100     | 100     | 100     | 100     |
| 7           | Track     | 2                | 100     | 100     | 100     | 100     |
| 7           | Straw     | 3                | 100     | 100     | 100     | 100     |
| 7           | Tire      | 3                | 94.79   | 91.66   | 88.54   | 90.1    |
| 7           | Tree      | 3                | 97.91   | 99.47   | 98.43   | 98.95   |
| 7           | Grass     | 4                | 96.09   | 96.09   | 99.6    | 99.6    |
| 7           | Rattan    | 4                | 98.82   | 99.6    | 100     | 100     |
| 7           | Sponge    | 4                | 98.82   | 99.21   | 100     | 99.6    |
| 7           | Tiles     | 4                | 98.82   | 98.43   | 99.6    | 100     |
| 7           | Building  | 5                | 90.31   | 92.18   | 92.81   | 92.81   |
| 7           | Leaf      | 5                | 93.43   | 95.62   | 94.68   | 94.06   |
| 7           | Styrofoam | 6                | 100     | 100     | 100     | 100     |
| 7           | Leather   | 7                | 93.35   | 93.16   | 91.01   | 91.21   |
| 7           | Plastic   | 8                | 97.46   | 97.07   | 98.63   | 98.63   |
| 7           | Food      | 10               | 90.93   | 92.81   | 93.43   | 95.78   |
| 7           | Paper     | 10               | 98.75   | 98.9    | 100     | 100     |
| 7           | Floor     | 11               | 83.59   | 86.87   | 87.96   | 89.84   |
| 7           | Rubber    | 11               | 95.15   | 96.25   | 97.81   | 97.81   |
| 7           | Bark      | 13               | 84.53   | 87.81   | 89.84   | 92.81   |
| 7           | Flower    | 13               | 83.43   | 85.31   | 89.21   | 90.31   |
| 7           | Marble    | 13               | 91.4    | 92.81   | 94.06   | 95.31   |
| 7           | Technic   | 14               | 82.96   | 85.93   | 87.03   | 87.81   |
| 7           | Hair      | 15               | 76.71   | 74.53   | 80.78   | 84.53   |
| 7           | Paint     | 15               | 96.87   | 97.96   | 99.68   | 100     |
| 7           | Bush      | 18               | 90.78   | 91.56   | 93.75   | 94.84   |
| 7           | Gravel    | 20               | 92.5    | 90.93   | 96.87   | 97.5    |
| 7           | Stone     | 29               | 79.53   | 83.75   | 83.12   | 86.71   |
| 7           | Wall      | 30               | 92.34   | 92.81   | 94.84   | 95      |
| 7           | Metal     | 31               | 88.28   | 89.53   | 90.62   | 91.87   |
| 7           | Wood      | 41               | 98.43   | 98.59   | 100     | 100     |
| 7           | Mise      | 44               | 94.21   | 93.43   | 97.18   | 98.12   |
| 7           | Fabric    | 77               | 98.59   | 97.56   | 99.84   | 100     |
Table (5): The Final Results of CM

| No. Feature | Class  | No. of Sub Class | Testing Data | Training data | Total Data |
|-------------|--------|------------------|--------------|---------------|------------|
| 7           | Porcelain | 2                | 100          | 100           | 100        |
| 7           | Track    | 2                | 100          | 100           | 100        |
| 7           | Straw    | 3                | 100          | 100           | 100        |
| 7           | Tire     | 3                | 96.54        | 94.79         | 95.665     |
| 7           | Tree     | 3                | 100          | 98.54         | 99.475     |
| 7           | Grass    | 4                | 100          | 99.6          | 99.8       |
| 7           | Rattan   | 4                | 100          | 100           | 100        |
| 7           | Sponge   | 4                | 99.9         | 99.6          | 99.75      |
| 7           | Tiles    | 4                | 100          | 100           | 100        |
| 7           | Building | 5                | 96.54        | 92.81         | 94.675     |
| 7           | Leaf     | 5                | 97.99        | 95.62         | 96.805     |
| 7           | Styrofoam| 6                | 100          | 100           | 100        |
| 7           | Leather  | 7                | 95.31        | 93.35         | 94.33      |
| 7           | Plastic  | 8                | 99.87        | 98.63         | 99.25      |
| 7           | Food     | 10               | 98.78        | 95.78         | 97.28      |
| 7           | Paper    | 10               | 100          | 100           | 100        |
| 7           | Floor    | 11               | 95.32        | 89.84         | 92.58      |
| 7           | Rubber   | 11               | 99.32        | 97.81         | 98.565     |
| 7           | Bark     | 13               | 97.85        | 92.81         | 95.33      |
| 7           | Flower   | 13               | 94.48        | 90.31         | 92.395     |
| 7           | Marble   | 13               | 97.09        | 95.31         | 96.2       |
| 7           | Technic  | 14               | 93.98        | 87.81         | 90.895     |
| 7           | Hair     | 15               | 95.98        | 84.53         | 90.255     |
| 7           | Paint    | 15               | 100          | 100           | 100        |
| 7           | Bush     | 18               | 99.65        | 94.84         | 97.245     |
| 7           | Gravel   | 20               | 99.96        | 97.5          | 98.73      |
| 7           | Stone    | 29               | 94.25        | 86.71         | 90.48      |
| 7           | Wall     | 30               | 97.99        | 95            | 96.495     |
| 7           | Metal    | 31               | 95.14        | 91.87         | 93.505     |
| 7           | Wood     | 41               | 100          | 100           | 100        |
| 7           | Misc     | 44               | 99.32        | 98.12         | 98.72      |
| 7           | Fabric   | 77               | 100          | 100           | 100        |
5.1 Conclusions

The classification based on GM gives a good description of the directional properties of the texture (horizontal, vertical, and diagonal direction). GM drives to the more accurate description to the texture than that done by CM set. The features extracted from Contrast matrices (CM) led to classification accuracy around (96%). The superiority of the set of CM features is due to taking into consideration the brightness in addition to roughness when calculating the texture attributes. Both GM and CM considered as a fast way to extract features rather than other way like DCT or DFT. The comparison between CM in blue line and GM in red line shown in figure (4), it’s clear that GM batter than CM as we mention earlier.

![Figure- 4 Comparison between CM, GM](image)

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