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A Comparative Study on Feature Extraction using Texture and Shape for Content Based Image Retrieval

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Abstract

Image Retrieval is the basic requirement of today's life in present scenario. Because of huge amount of different types of images are added in database from different sources for retrieval of the image, different kinds of processing is required to extract the relevant features from them. In this paper, comparisons of combination texture and shape features are done with texture Gray Level Co-occurrence Matrix and Hu-moments and the combination of tamura texture and shape invariant Hu-moments. For the performance evaluation of the system we use most commonly used methods namely precision and recall.

Keywords: *Content Based Image Retrieval (CBIR), Gray Level Co-occurrence Matrix*

1. Introduction

In recent years image processing is used for multimedia database for storing digital images and also based on digital image processing which is the application of computer based algorithms. Image Retrieval aims at developing techniques browsing large image digital libraries to find out whether an image or the image database contains the query pattern given by the user on the basis of similarity measures. Image Retrieval is basically based on two approaches Text Based Image Retrieval (TBIR) [1] and Content Based Image Retrieval (CBIR). Text Based means of given image annotation which provides the information given for the images. Text Based Image retrieval techniques based on textual annotation of images and these are based on two steps, firstly the images were annotated with text, and secondly the images are searched based on their textual tag or keywords actions which used by the users for searching such images. In context to Text Based, retrieving image is fast and also reliable but it is over dependent on labeling which is subjected to human perception. There are many limitations with Text Based techniques due to their reliable on manual annotation, in case of large dataset it become more difficult to find out(error prone)by this process. To overcome the limitations of TBIR, concept of Content Based Image retrieval was proposed and these are effectively used by the people, such as Query Based Image Retrieval.

Content Based Image Retrieval (CBIR) [2] is a kind of Image Retrieval technique that could figure out images like sketch similar to querying images from image database. Image features are extracted based on content and these features like color and shape can be used to retrieve the images from the large database based on some similarity measures. In Content Based Image Retrieval (CBIR) image can be retrieved by query known as Query by Image Content and also known as content Based Visual Information (CBVI) which is the application of Computer Vision techniques for the problem of searching digital images from large image database known as image retrieval problem. A typical CBIR system consists of four main steps. Firstly, the most basic process of CBIR system is feature extraction in which extract the features of image like from spatial based on

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pixels. Secondly, the system will characterize those selected feature spaces and the construct the feature vectors. Thirdly, these feature vectors of query image are compared with images stored in database. Finally, the output queried image results to the similar images to the query images based on computing some similarity measures. Then performance evaluation of the system is done we use most commonly used methods namely, precision and recall. The main issues in CBIR system arises which features should be derived to describe the images better within the database and which data structure be used to store the feature vectors .And most important which learning algorithms should be used in order to make the CBIR efficient. And finally, most important at the retrieval time is how to participate according to user's feedback in order to improve the result.

2. Related Work in this Field

Kato, T. [3] in 1992, National Science Foundation of United States organized a workshop on visual information management system in order to identify a new direction in image Database Management System introduced the term Content Based Image Retrieval, and they emphasized the use of color and shape as the most important criteria of feature extraction for image retrieval system. Since, and then the CBIR has been adopted as to describe an image retrieving process.

Tamura *et al.*, [4] in 1973, proposed texture representations that were based on psychological studies of human perception, and these representations consists of six statistical features, including coarseness, contrast, directionality, regularity, line-likeness, roughness to describe various texture properties. In context to texture features extraction tamura properties are very meaningful and this advantages makes tamura features in Texture Based Image Retrieval. In comparison with psychological measurements for human subjects, the computational measures gave good correspondence in correlation of rank of 16 patterns of typical texture type of patterns. These features were attempted by using similarity measurements.

A. Rosenfield *et al.*, [5] in 1976 applied features and used three standard approaches to automatic texture classification make used these based on Fourier Power spectrum respectively, and these applied features to a set 54 picture samples taken from aerial photographs of nine terrain types (Lakes, Orchard, Railroad and woods *etc.*,). Classification results of these types were compared for individual features and pairs of features with each feature class. In general, the Fourier based features performed poorest, while those based on statistics of gray level differences performance's best.

Haying Zhao *et al.*, [6] in 2009, proposed textural feature extraction based on coarseness .To improve the performance they used coarseness textural feature and compared its result with the Gray Level Co-occurrence Matrix textural coarseness, Fractual dimension textural coarseness and tamura textural model. And they proposed amongst the three, tamura textural model performance of describing coarseness is best followed by the other two methods.

Yao *et al.*, [7] in 2003, proposed a retrieval system using Gray Level Co-occurrence Matrix and applied sobel detector, edge detection one of the method by texture segmentation since by considering only texture properties like coarseness energy, some of the information is loss .So they proposed the combination of both texture segmentation method edge detection and texture properties, got the high retrieval of precision value.

H.-C. Lin *et al.*, [8] in 2003, proposes a fuzzy logic CBIR system for finding textures. In this CBIR system, a user can submit textual descriptions and /or visual examples to find the desired textures. After the initial search, the user can give relevant and/or irrelevant examples to refine the query and improve the retrieval efficiency.

Jing Zhang *et. al.*, [9] in 2008, proposed image retrieval by texture characterization by GLCM texture properties and an edge detector by prewitt edge detection, since by considering the texture properties only coarseness, contrast, energy correlation there is much information left on the edges. Thus they proposed the composition of both the co-occurrence matrix and the edge detector approach, and they used composition of edge information and texture characterizations of GLCM properties and proposed the method which has high retrieval precision.

Jing Zhang *et al.*, [10] in 2010, used feature extraction and proposed Color Co-occurrence (CCM) matrix based on Gray Level Co-occurrence Matrix extract features from any one of the color plane for each plane and proposed image retrieval based on multi-fusion on GLCM and color, and retrieved the texture characteristics based on color space HSV based image retrieval, using similarity measures like Euclidean distance .They proposed CCM textures features and color composition with CCM improves the performance of image retrieval which is the important research value.

Nikhil Chaturvedi *et al.*, in [11] proposed CBIR based on texture features contrast, coarseness, directionality statistical features. They firstly proposed the feature vectors based on texture is extracted from the query image then the similarity measurement algorithm is applied to the extracted feature vector from which relevant images are retrieved from the database.

N. Puviarasan *et al.*, [12] in 2014 proposed Retrieval of images from large databases from the image database using CBIR technique. The proposed a combination of texture and shape feature extraction methods like Haralick features and Hu-invariant moments. They first segment the image according to the Fuzzy C-means clustering and comparing with the k-means, and they extracted features according to the texture and shape and use the combination of both features. The corel images database were used for experimentation. And similarity measures Euclidian distance was applied for the retrieval of images.

Peter *et al.*, [13] in 2004 compared the three textures features GLCM, tamura and Gabor filter .based on query-by-example approach to image retrieval. The features calculated were evaluated and tested on retrieval tasks from the corel TREVID 2003 images collection. They found that tamura performs better than other two features but for large scale coarseness degraded performance and therefore they limited the range and used a logarithmic scale.

Thomas *et al.*, [14] in 2007 experimental comparisons of large number of descriptor images for CBIR. The methods proposed earlier descriptors for CBIR describes their newly proposed methods as most appropriate methods. In this paper a large number of features for CBIR are done, and compared them quantitatively on different tasks. These comparisons of features were done on five different publicly freely available image databases, and the retrieval performance is used. This method allow to used a direct comparisons of all features considering and further in future will allow a comparisons of newly proposed features to these in future.

3. Feature Extraction

Feature extraction plays an important role in Image Retrieval system and better selection of feature gives higher accuracy. Feature extraction is basically it separates the visual information from the image and stores them in the form of feature vectors in a feature database. These feature value (or a set of values) called feature vectors of image finds the image information from the feature extraction. These feature vectors are used to compare the query image with the images stored in the database. In the field of pattern recognition, features can be characterized as a way to distinguish one class of object from another. In CBIR when features are extracted then the most important problem in which feature selection the most relevant images are obtained.

Feature extraction like color, texture and shape. Each feature may have several representations and different representations aspects of the feature when designing an image retrieval system. Texture features like Tamura six features, first-order intensity histogram based features, Haralick features and shape features like Hu-moment.

3.1. Feature Extraction Based on Texture

Texture is a very important characteristics for the analysis of many types of images that appears everywhere in nature like natural images, remote sensing images and medical images [15]. Texture can be defined as superficial phenomenon of human visual systems of natural objects. Texture can be attributed to almost everything in nature and also its texture structure of any image is incorporating repeated pattern of all most all of the parts. Texture is commonly known as 'texels'. Texture can be recognized by everyone but it is not easy to define. Texture does not occur over a point but it rather occurs over a region. Texture can be analyzed by quantitative and qualitative analysis.

3.1.1. Tamura Texture Feature

According to quantitative analysis one of the first descriptions given by the Tamura [4] proposed six textural properties and gave descriptions common over all texture patterns in Broadtz's photographic images. These are six different texture features given by tamura Coarseness, Contrast, Directionality, Line-Likeness, Regularity and Roughness.

- Coarseness

Coarseness basically relates to the distance in gray levels of spatial variations, which is implicitly related to the size of primitive elements forming the texture. It has the direct relationship to scale and repetition rates and most fundamental texture feature. An image will contain repeated textures pattern at different scales, coarseness aims to identify the largest size at which a texture exists, even where a smaller micro texture exists.

$$A_k(x,y) = \sum_{i=x-2k-1}^{x+2k\_1} \sum_{j=y-2k-1}^{y+2_{k-1}-1} \frac{f(i,j)}{2^{2k}} \tag{1}$$

Where, $2^k * 2^k$size is the average of neighborhood.

$$E_{k,h}(x,y) = |A_k(x+2_{k-1},y) - A_k(x-2_{k-1},y)| \tag{2}$$

This equation (2) calculates the difference between pair of averages corresponding to non-overlapping neighborhoods.

- Contrast

Contrast measures distribution of gray levels that varies in an image and to what extent its distribution is biased to black or white. The second order and normalized fourth–order central moments of the gray levels are used to define the contrast.

$$Contrast = \sigma/(\alpha_4)$$

$$\alpha_4 = \mu_4/\sigma^4 \tag{3}$$

where, μ_4 is the fourth moment about the mean and σ2 is the variance. n=1/4 to give the closest value according to tamura.

- Directionality

Directionality of an image is measures by the frequency distribution of oriented local edges against their directional angles. It is a global property over a region. This texture feature given by tamura does not differentiate between orientations or patterns but measures the total degree of directionality in an image is given by Directionality. It is the most important feature given by tamura about matrix to distinguish from another image that how much uniform the region is.

$$\mathrm{Directionality} = 1 - \mathrm{rn}_{\mathrm{peaks}} \sum_{\mathrm{p}=1}^{\mathrm{n}_{\mathrm{peaks}}} \sum_{\mathrm{a}\epsilon\mathrm{w}_{\mathrm{p}}} \left(\mathrm{a} - \mathrm{a}_{\mathrm{p}}\right)^2 \mathrm{H}_{\mathrm{directionality}}(\mathrm{a}) \quad (4)$$

where, n_{p}, number of peaks, a_{p}, is the position of the peak, w_{p}, is the range of the angles attributed to the Pth peak, r denotes a normalizing factor related to quantizing levels of the angles a, and a denotes quantized directional angle, $H_{Directionality}$, is the histogram of quantized direction values ,a is constructed by counting number of the edge pixels with the corresponding directional angels.

- Line-Likeness

Line-Likeness in an image is average coincidence of direction of edges that co-occurred in the pairs of pixels separated by a distance along the edge direction in every pixel.

- Regularity
  Regularity measures a regular pattern or similar that occurred in an image.

$$\mathrm{F}_{\mathrm{regularity}} = 1 - \mathrm{r}(\mathrm{S}_{\mathrm{crs}} + \mathrm{S}_{\mathrm{con}} + \mathrm{S}_{\mathrm{dir}} + \mathrm{S}_{\mathrm{lin}} \quad (5)$$

- Roughness
  Roughness is the summation of contrast and coarseness measures.

Roughness= Contrast + Coarseness

In most of the cases, for CBIR system only first three features are used because these features capture the high-level perceptual attributes of a texture and are also useful for browsing of images.

3.1.2. Haralick Texture Feature

Gray Level Co-occurrence Matrix (GLCM) a statistical method for examining texture features that consider the spatial relationship of pixels, also known as Gray Level Spatial Dependence. In this a GLCM matrix is created by calculating how often a pixel with the intensity value i occurs in a specific spatial relationship to a pixel with the value j. GLCM consists of frequencies at which two pixels are separated by a certain vector occur in the image. GLCM properties by which the distribution in the matrix will depends on the distance and angular or directions like horizontal, vertical, diagonal, anti-diagonal relationship between the pixels. Many statistical features of texture in an image are based on the co-occurrence matrix representing the second order of gray levels pixels relationship in an image. Various statistical and information theoretic properties of the co-occurrence matrices can serve as textural features and the limitation with these features are expensive to compute , and they were not very efficient for image classification and retrieval. Haralick [16] proposed 28 kinds of textural features each extracted from the Gray Level Co-occurrence Matrix. Suppose an input image has M total number of pixels in horizontal directions and M total number of pixels in vertical directions. Suppose the gray level that appears at each pixel is quantized to z number of levels, assume Nx =1,2,3,…….M consists of horizontal space and Ny=1,2,3…….N consists of vertical space and G =0,1,2,3…Z consists of the set of Z quantized gray levels. In a given distance d and direction given by θ, the Gray Level Co-occurrence matrix is calculated by using gray scale pixel i and j, expressed as the number of co-occurrence matrix in different directions.

$$P(i,j|d,\theta) = \frac{p(i,j|d,\theta)}{\sum_i \sum_j p(i,j|d,\theta)} \quad (6)$$

Among them five features Contrast, Correlation, Entropy, Energy and Homogeneity.

Contrast

Contrast measures intensity between a pixel and its neighbor over the whole image and it is considered zero for constant image and it is also known as variance and moment of inertia.

$$\text{Contrast} = \sum_{i,j}(i-j)^2 p(i,j) \quad (7)$$

- Correlation

Correlation measures how pixel is correlated to its neighbor over the whole image.

$$Correlation = \sum_{i,j}\frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\delta_i\delta_j} \quad (8)$$

- Entropy

Entropy gives measures of complexity of the image and this complex texture tends to higher entropy.

$$Entropy = \sum_i\sum_j P(i,j) \quad (9)$$

- Energy

Energy is the sum of squared elements in the GLCM and it is by default one for constant image.

$$Energy = \sum_{i,j}(i,j)^2 \quad (10)$$

3.2. Feature Extraction Based on Shape

3.2.1. Hu-Moment Shape Features

Hu-Moment [17] in 1962 proposed seven properties related to connected region that are invariant to rotation, scaling, and translation (RTS) and are also known as Algebraic Moment Invariants. Moment invariants that are computed from each of the window are used to form feature vectors. They define simply calculated set properties of region that can be used for class identification and also identification of shape, and this classic technique for generating invariants in terms of algebraic was originally proposed by Hu.

Suppose R is a image, p + q, central moments or R forms as

$$\mu_{p,q} = \sum_{x,y}(x-x_c)^p(y-y_c)^q \quad (11)$$

(x_c, y_c) is the centre of object .For scale –independent nature ,central moments can be standardized as

$$\eta_{p,q} = \frac{\mu_{p,q}}{\mu_0^2,0}$$

$$\gamma = \frac{p+q+2}{2}$$

Based on these moments, Hu bring forward seven moments independence of translation, rotation and scaling.

$$\emptyset_1 = \mu_{2,0} + \mu_{0,2} \quad (12)$$

$$\emptyset_2 = (\mu_{2,0} - \mu_{0,2})^2 + 4\mu_{1,1}^1 \quad (13)$$

$$\emptyset_3 = (\mu_{3.0} - 3\mu_{1,2})^2 + (\mu_{3,0} - 3\mu_{2,1})^2 \quad (14)$$

$$\emptyset_4 = (\mu_{3,0} + \mu_{1,2})^2 + (\mu_{0,3} + \mu_{2,1})^2 \quad (15)$$

$$\emptyset_5 = (\mu_{3,0} - \mu_{1,2})(\mu_{3,0} + \mu_{1,2})[(\mu_{3,0} + \mu_{1,2})^2 - 3(\mu\_2{,}1 + \mu\_0{,}3\ )^2] + (3\mu_{2,1} - \mu_{0,3})(\mu_{2,1} + \mu_{0,3}).[3(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2 \quad (16)$$

$$\emptyset_6 = (\mu_{2,0} - \mu_{0,2})\left[(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2\right] + 4\mu_{1,1}(\mu)(\mu_{2,1} + \mu_{0,3}) \quad (17)$$

$$\emptyset_7 = (3\mu_{2,1} - \mu_{0,3})(\mu_{3,0} + \mu_{1,2})\left[(\mu_{3,0} + \mu_{1,2})^2 - 3(\mu_{2,1} + \mu_{0,3})^2\right] - (\mu_{3,0} - \mu_{1,2})(\mu_{2,1} + \mu_{0,3})[3(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2] \quad (18)$$

$\emptyset_7$, is the skew moment, and this skew invariant is useful in distinguishing mirror images. These moment used in feature extractions can be generalized to accomplish pattern identification not only, independent of position, size and orientation but also independently of parallel projection.

4. Proposed Methodology

Before analyzing images based on their feature extraction from databases of images, pre-processing methods in images are performed in all types of images. Like, firstly, the images resize according to the region of interest for the faster retrieval of images. Deleting and removing complicated background will speed up further image processing.

Texture [18], very strong discriminative power feature makes an essential component in image and video retrieval. Tamura six texture features in which directionality most important feature based on human perception. Therefore, it is very important to find an effective method to compute the directionality of an image, and tamura uses statistical measure to calculate statistical feature. Therefore we use the shape moment given by Hu [17] which are invariant. And thus we extract texture features and shape and fused these feature vectors of tamura and shape combinations for better result.

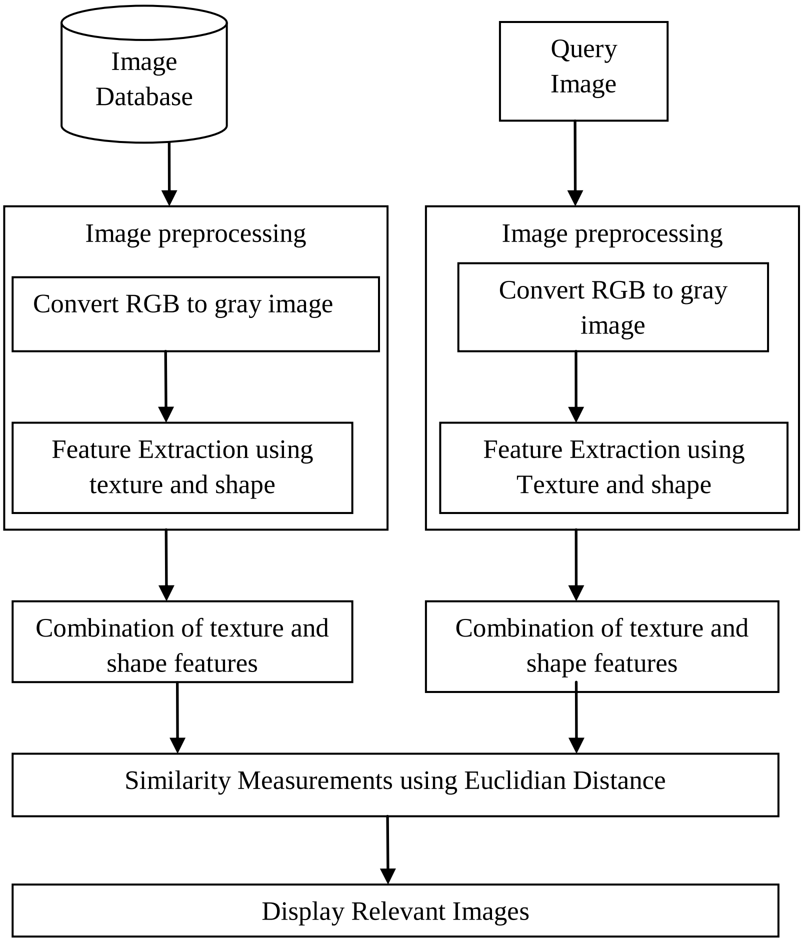

Figure 1. Proposed Methodology of CBIR

4.1. Algorithm for Proposed Methodology

Step1: Input the query image

$$Input = Iquery$$

Step2: Perform the image pre-processing in an input image.

Step3: Convert image from RGBtoGray.

Step4: Extract the texture and shape features form the feature vector.
Feature vector = [Contrast, Energy, Correlation]
Feature vector = [moment1, moment2, moment3]

Step4: Fused the combination of texture and shape feature vector into a single feature vector.
Feature vector = [contrast, energy, correlation, moment1]

Step5: Apply similarity measurement algorithm, Euclidian distance to the extracted feature vector and the feature vectors of image Database stored in database.

Step6: Retrieve the relevant images based on some similarity measures from images stored in Database.

5. Similarity Measurement

A. Euclidian Distance

Euclidian Distance [19] matrix is mostly used for similarity measurement in context retrieval of image from database because of its higher accuracy and effectiveness. It measures the distance between the two feature vectors of images by calculating the square root of the sum of the squared absolute differences and is calculated and is denoted by ED.

$$\mathrm{ED} = \sqrt{(\sum_{i=1}^{n}(|Q_i - D_i|)^2)} \qquad (19)$$

6. Experimental Results

The proposed method is tested by using the Broadtz [20] database of images, which is freely available for researchers. Broadtz database consists of categories like bricks, stones, grass etc. of grayscale images. Retrieval has been classified as accurate if, for a given query image the system retrieved according to human perception the most similar images from the database are obtained. According to human perception in image retrieval the more the precision value the higher the performance.

Table 1. Performance Evaluation Method

Method	Euclidian Distance			
	Tamura+ Hu-Moment		GLCM+ Hu-Moment	
Type of Textures	**Precision**	**Recall**	**Precision**	**Recall**
Bricks	.78	.88	.67	.75
Stone	.78	.87	.67	.75
Grass	.68	.87	.66	.76
Grills	.78	.87	.67	.75

In Table 1 the performance evaluation method using precision and recall is shown .The result comprises of the comparison of combination of texture and shape. The table consists of four different types of images and the precision and recall value are shown. The comparison of tamura and Hu-moment gives better result than GLCM and Hu-moment is shown .And this result is shown in Figure 4 in form of Bar graph also. In Figure 2 the query image is shown and in Figure 3 the relevant images are shown of the proposed method. In Table 2 average performance evaluation methods of precision and recall value is shown of the compared methods.

Figure 2. Input Image

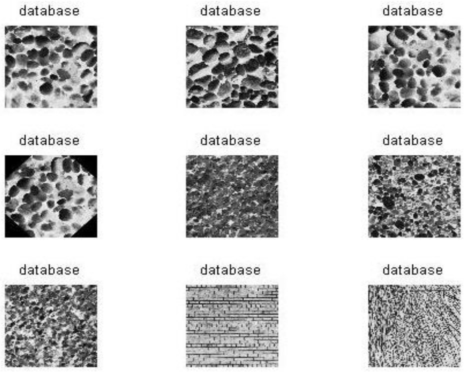

Figure 3. Comparison between Combination Texture and Shape Method

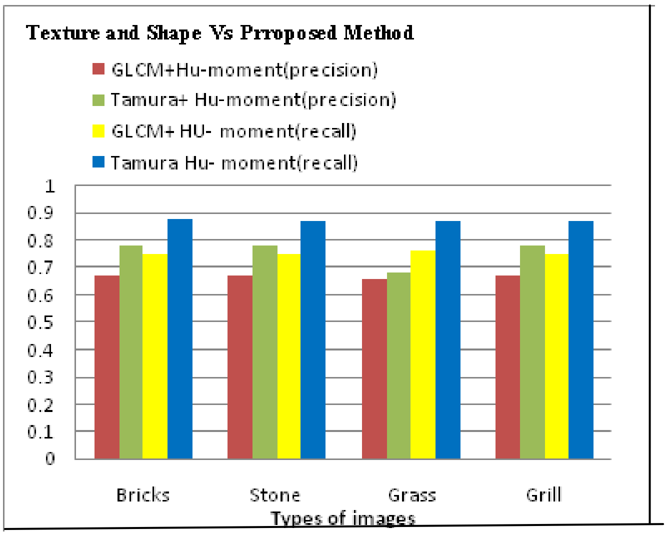

Figure 4. Performance Evaluation Method

In Content Based Image Retrieval System Precision is the most important criterion of evaluation system to find the accuracy of the images retrieved. The precision P and recall R for a query image is defined as follow

$$\text{Precision} = \frac{\text{No.of Relevant Images Retrieved}}{\text{Total no.of images retrieved}} \tag{20}$$

$$\text{Recall} = \frac{\text{No.of Relevant Images Retrieved}}{\text{Total no.of relevant images in database}} \tag{21}$$

Table 2. Average Performance Evaluation Table

Methods	Euclidian Distance	
Texture and Shape Feature	Precision	Recall
GLCM+ Hu-Moment	0.67	0.75
Tamura + Hu-Moment	0.78	0.87

7. Conclusion

In this paper there are different textures and shape feature extraction techniques have been discussed. The main objective of content based image retrieval is to develop is an efficient image retrieval scheme. A comparison is performed between different textural and shapes features are combination of GLCM textural properties and Hu-moment, and tamura textural properties and shape Hu-moment. The combination of tamura textural and shape Hu-moment feature vectors perform better than combination of GLCM Textural and shape moment invariant given by Hu. The result can be further improved by using KNN K-Nearest Neighbor classifier at preprocessing step which gives better result at the retrieval time. Support Vector Machine, Soft computing techniques like neural network can be also applied as a classifier to improve the retrieval time. Evolutionary algorithms can also be used to optimize the result for the better feature selection process.

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