Analysis of Different Similarity Measures in Image Retrieval Based on Texture and Shape

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Abstract – *In the previous few years, large number of digital images are used in various application areas. To store and retrieve these images we need some efficient image retrieval techniques. Content Based Image Retrieval is one of the image retrieval system, but to develop a CBIR system with appropriate combination of low level features is a big problem. One another problem with CBIR system is to choose the effective similarity measure. In this paper, comparison is done between different similarity measures. Number of similarity measures are applied on combination of texture and shape based features. Here, Euclidian, Manhattan, Minkowski and Spearman distance measures are used as similarity measurement and applied on the combination of Local Binary Pattern and Edge Histogram Descriptor. For performance evaluation Precision and recall are used.*

***Key Words*:** Content Based Image Retrieval, Local Binary pattern, Edge Histogram Descriptor, Similarity Measurement

1. INTRODUCTION

Now a day, with the rapid growth of digital images, large number of digital images are used in different application areas such as- government, commerce, academics, hospital, crime prevention, engineering, architectures uses information in form of images. So we need to store and retrieve this information in an efficient way. To retrieve these images, we need to use some search engines to search the images among the database. But the main problem with this search engines is, it will not provide the proper result. To solve this problem image retrieval techniques are used. There are two types of image retrieval techniques, Text Based and Content Based. Text Based Image Retrieval (TBIR) is based on textual annotation of images. In TBIR images are labeled with some keywords and numbers and then searched using these text or keywords from the traditional databases. TBIR use traditional databases to manage images. TBIR is a reliable and fast image retrieval technique but for the large databases it is inefficient and time consuming because of its manual annotation. Other problem with TBIR is human perception means every people have different view on different images. To overcome these types of issues in text based system, another approach Content Based Image Retrieval (CBIR) was proposed CBIR use the visual information of image to search image from the databases according to user interest. In CBIR multidimensional feature vector are used to store the features exacted from the images and these feature vector are stored in the databases. To retrieve these images a query is given by the user in the form of sketch or digital image. CBIR system is also called as Query by Image Content or Query by Visual Information. There are different steps are used in CBIR system-

(a) Query by example
(b) Feature extraction
(c) Similarity measurement
(d) Performance evaluation

Query by example- In this query is given by the user in the form of sketch or digital image.
Feature extraction- In this step extraction of features in form of spatial information and these features are stored in feature vector.
Similarity measurement- In the similarity measurement feature vector of query image is compared with the feature of images in the database.

2. LITERATURE REVIEW

In 1992, Kato T introduced the concept of CBIR in a workshop on visual information management system organized by National Science Foundation of US. He used color and shape feature for retrieval of images. Since then CBIR has been used to describe an image retrieving process.

In 2000, Chee Sun Won [3] proposed an efficient use of MPEG-7 Color Layout and Edge Histogram Descriptors in CBIR Systems.

In 2011, S. Joseph et al. [41] proposed a method that retrieves similar images from the database of Malayalam handwritten characters. This method use Local Binary Pattern feature to extract a feature vector from the query image and compare it with the database images for retrieving the desired character images. This method gives excellent performance with Local binary Pattern.

In 2014, S. Bougueroua and B. Boucheham [42] proposed an approach based on region-based system for color images and Local Binary Pattern for texture feature present in the grayscale images. A set of ellipses, generated by rotation and contraction are superposes for covering the image. Each ellipse makes a region on LBP map. For each region one LBP-histogram is calculated. Finally texture image is represented by m LBP-histograms, where m is the number of region created by ellipse. Each region of query image is compared with the database images. Afterward a global distance between query and target images is derived. Afterward a global distance between query and target images is derived.

In 2015, Neelima Bagri and Punit k. Johari [10] surveyed the texture and shape based features for analyzing the image. In this paper, several features of texture and shape are described and give the comparative study between them.

2. FEATURE EXTRACTION

For retrieving the images feature extraction on the basis of visual features is a crucial task. Feature extraction is a crucial task for image retrieval using visual features of an image. Feature extraction is based on the extraction of visual feature of the image. Higher-dimensional Feature vector are used to store these visual features, stored these features in the database. In this research, we introduce a new combination of texture and shape based features. A feature that is extracted from image describes actual content of that image. These features are used as a signature of the image. Some images that are similar to each other should have same information or same signature. Corner, line, texture, color and shape are some features are used to describe an image. These features are stored in the feature vector in a feature database.

2.1 Texture Bases Feature Extraction

The texture is an important property for analysis of images. Textures are the visual pattern in an image that has a property of homogeneity. [17] Texture gives the structural information of surfaces and object of the image. Texture patterns depend on the distribution of intensity of the image. It can be analysed by the qualitative and quantitative analysis.

2.1.1 Local Binary Pattern

T. Ojala et al. [19] was proposed a method for feature extraction based on the binary pattern of an image is known as Local Binary Pattern. It is a multiresolution, gray scale and rotation invariant operator that is used for describing local pattern of an image. LBP calculate patterns like point and edges of a gray scale image. For constructing LBP, first image is converted into gray scale image and then need to calculate the center pixel. Local Binary Pattern is calculated by taking the difference between center pixel and its surrounding neighbour pixels [25]. It start from top left pixel and then it can work in any direction clock wise or anti-clock wise but ordering must consistent for all pixels in image. If the center pixel and its neighbour is smaller than the neighbour then it will put "1" otherwise it will put "0" [29]. The value is return in binary digit and weight is associated with these binary digits. LBP is calculated by using given equation:

$$LBP_{P,R} = \sum_{P=0}^{P-1} s\left(G_p - G_c\right) 2^P$$

(1)

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

(2)

Computation of LBP is shown below:

Example

8	9	11
3	5	7
2	0	16

Binary Pattern

1	1	1
0		1
0	0	1

Weights

1	2	4
0		8
0	0	16

LBP Value

	31	

$LBP = 2^0*1+2^1*1+2^2*1+2^3*1+2^4*1+2^5*0+2^6*0+2^7*0=31$

Where,

Gc = Gray level value of center pixel

Gp = Gray level value of neighbour pixel

P = Number of neighbours

R = radius of center pixel

2.2 Shape Based Feature Extraction

A shape is the most significant feature of image retrieval. It plays an essential role in human perception and objects recognition. Usually, shape feature is described after segmentation of an image into sub-images. In this paper, Edge Histogram Descriptor is used to extract edges of an image.

2.2.1 Edge Histogram Descriptor

Edge histogram descriptor (EHD) [3] [7] is used as a shape as well as color based descriptor. It provides geometric information in case of same image have different color. It is a spatial spreading of 5 types of edges Horizontal, vertical, 450 diagonal, 1350 anti-diagonal and non-directional in each sub-image. The sub-image is described by dividing an image into 4x4 non overlapping blocks. Histogram is generated by each pixel of sub-image. Sub-image is then additionally divided into number of image blocks to describe the distribution of edges. It represent the frequency of occurrence in five types of edges in each sub-block.

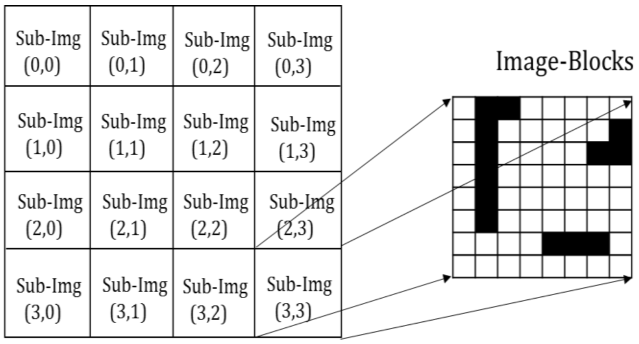

Fig -1: Define the sub-image and image block

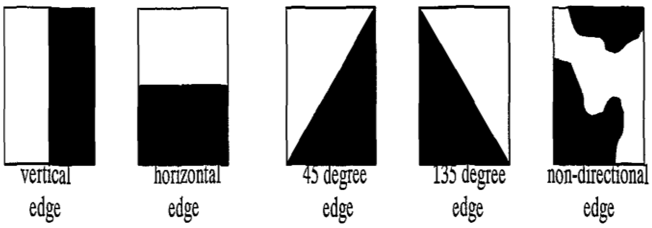

Fig -2: Five types of edges

a. Semantics of Local Edge Histogram

After extraction of edges from image-blocks we count the total number of bins in each edge type in sub-image. We define five histogram bins for each sub-image called as Local edge histogram. There are total 16 sub-images so total number of bins are 16x5=80.

Table -1: Semantics of Histogram Bins

Histogram Bins	SEMANTICS
Local-Edge[0]	Vertical Edge at (0,0)
Local-Edge[1]	Horizontal Edge at (0,0)
Local-Edge[2]	45 Degree Edge at (0,0)
Local-Edge[3]	135 Degree Edge at (0,0)
Local-Edge[4]	Non-Directional Edge at (0,0)
.	.
.	.
Local-Edge[76]	Vertical Edge at (3,3)
Local-Edge[76]	Horizontal Edge at (3,3)
Local-Edge[77]	45 Degree Edge at (3,3)
Local-Edge[78]	135 Degree Edge at (3,3)
Local-Edge[79]	Non-Directional Edge at (3,3)

b. Non-Normative Global Edge Histogram

For better performance local edge histogram is not enough, it also need edge distribution for whole image. Five histogram bins used for edge distribution of image globally called as global edge histogram. We have total [16x5=80 bins + 1x5 bins] 85 bins for edge histogram.

To calculate directional edge strength for each edge type, if the maximum out of them is greater than threshold value (Tedge), then image block is considered otherwise it considered no edge.

$$\mathrm{Max}\{m_v(i,j), m_h(i,j), m_{d-45}(i,j), m_{d-135}(i,j), m_{ND}(i,j)\} > T_{edge}$$

3. PROPOSED METHODOLOGY

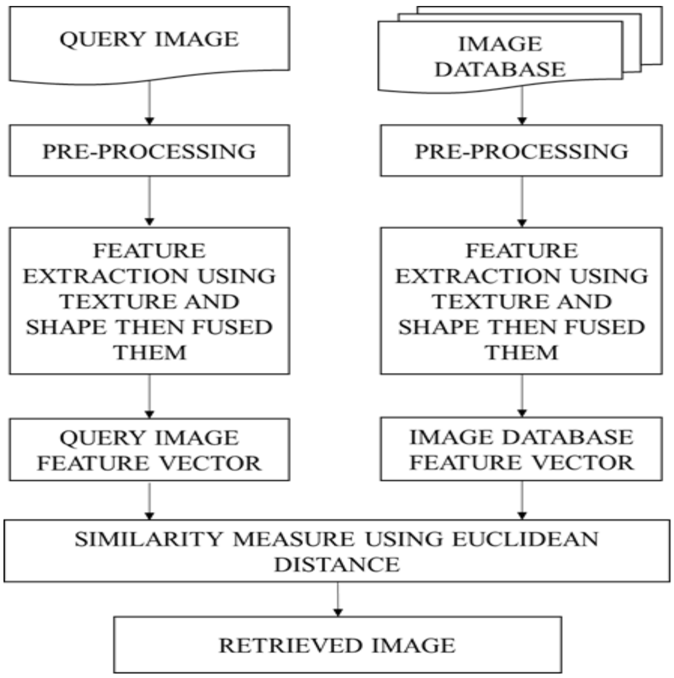

Fig -3: Flowchart of Proposed Methodology

3.1 Proposed Algorithm

Step1: input the query image.

Step2: Pre-processing on the image. First, resize the image into 256*384 and then convert the image into RGB to gray.

Step3: Apply local binary patter and edge histogram descriptor on input image.

Step4: Feature Vector = [LBP]

Feature Vector = [Edge Histogram Descriptor]

Step5: Combine both feature vectors into a single feature vector.

Step6: Apply different types of similarity distance to compare query image feature vector and database image feature vector.

Step7: On the basis of similarity measure ranked images from most relevant to irrelevant, then retrieve top ranked images.

5. EXPERIMENTAL RESULT

5.1 Similarity Measurement

The similarity measure is a significant task for retrieval of images from the database that is similar to query image. Retrieval performance of retrieval system also depends on the similarity measurement of the database image feature vector and query image feature vector.

a. Minkoswki Distance

Minkowski [36] is widely used matric for retrieval of image in which each direction of image feature vector is not dependent to each other.

$$D(i,j) = \left(\sum_i |f_i(I) f_i(j)|^p\right)^{1/p} \quad (3)$$

b. Euclidian distance

Euclidian distance [36] is most widely used similarity measure. The Euclidian distance measures is used to calculate the distance between the query image and database image.

$$D = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \quad (4)$$

Where x_i is the feature vector of the query image and y_i is the feature vector of images in the database. D is the similarity distance between the query image and database image and k represent the total number of element in each feature vector.

c. Manhattan Distance

Manhattan [27] [36] is a most widely used distance measure to calculate difference between feature vector of query image and feature vector of each database image.

$$Dm(q,i) = \sum_{j=1}^{n} |f_{qj} - f_{ij}| \quad (5)$$

Where, q is the query image, I is the database image and j is the feature vectors from j equal to 1 to n. we find the summation of difference between feature vector of query image and feature vector of database image. Manhattan is also called as city block distance.

d. Spearman rank coefficient

Spearman rank coefficient is used for measure the similarity between query image feature vector and database image feature vector. Spearman rank coefficient [36] is defined as:

$$D(x,y) = 1 - \frac{6\sum_{j=1}^{d}[R(x_i) - R(y_i)]^2}{d(d^2-1)} \quad (6)$$

Where $R(x_i) - R(y_i)$ is the difference between rank of feature vector of query image and feature vector of image database.

5.2 Experiment Database

In proposed system, WANG database [35] is used. WANG database has 1000 images with 10 classes, each class has 100 images. We used 600 images of 6 classes. These are Africans, Beach, Architecture, Buses, Dinosaurs and Horse. Each category having 100 images approximately.

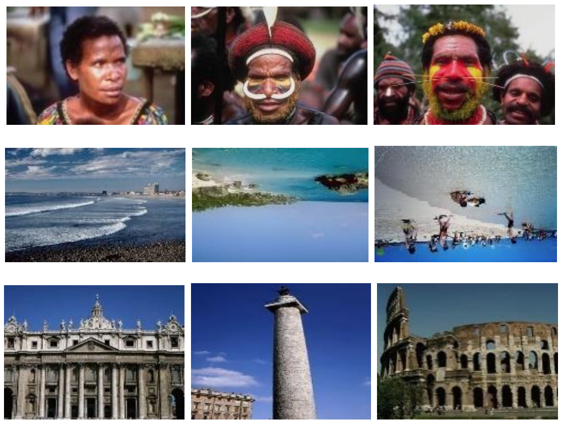

Fig -4: Four Image Semantic Types

5.3 Performance Evaluation Matrics

There are a number of evaluation matrices are used to evaluate the retrieval performance [21]. For matric evaluation, we are using precision and recall. Where, precision measure the availability of relevant images from the retrieved image in CBIR system and recall measure the availability of relevant images from the retrieved image over the total number of relevant images in the database.

$$Precision = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ \ Number\ of\ images\ retireved}$$

$$Recall = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ in\ database}$$

5.4 Results

To analyses the visual similarity of CBIR system, various types of distance measures are used. We took some random images from each class and applied these images one by one and retrieved top 40 images. Then calculate average precision and average recall for every class. Result shown that Manhattan and spearman rank coefficient distance measure provided the better result in comparison of Euclidian and Minkowski distance measure. In most of classes Spearman give the better result than Manhattan.

Table -1: Comparison Result

LBP+EHD								
Methods	**Euclidian**		**Manhattan**		**Minkowski**		**Spearman**	
Types of Database	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Africans	0.84	0.336	0.88	0.352	0.83	0.332	0.86	0.344
Beach	0.48	0.192	0.64	0.256	0.50	0.200	0.54	0.216
Building	0.28	0.112	0.54	0.216	0.47	0.188	0.57	0.228
Buses	0.69	0.276	0.82	0.328	0.69	0.276	0.71	0.284
Dinosaur	0.82	0.328	0.98	0.392	0.80	0.320	1	0.400
Horses	0.74	0.296	0.62	0.248	0.75	0.300	0.76	0.304
Overall Average	0.64	0.256	0.74	0.296	0.67	0.268	0.74	0.296

In Figure 4 shows comparison between combination of Local Binary Pattern and Edge Histogram descriptor with different types of similarity measures.

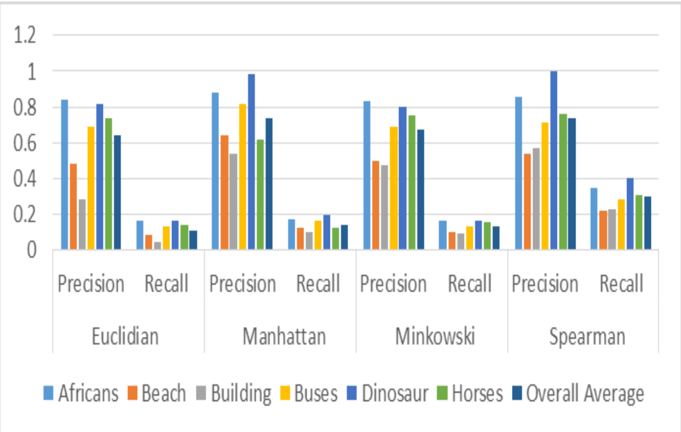

Chart -1: Comparison Graph

6. CONCLUSION

In this paper, different types of distance measure techniques are described. The main purpose of this paper to analyze the performance of different similarity measures. Here, Euclidian, Manhattan, Minkowski and Spearman distance measure applied on texture and shape based features. We find that Spearman rank coefficient produced the better result in comparison with other distance measures.

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