Image Retrieval System Using Fusion of Texture Features with Various Distance Metrics

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ABSTRACT

Abstract- *From last few years, the need of massive database used to store vast images has been developed rapidly and will also grow in the future. Content Based Image Retrieval System (CBIRS) provides us at most outcome to fetch the images from massive dataset. We present the proposed work which is "Fusion of CBIRS using Color and texture with various distance metrics". In these systems, two features like Color and Texture are used to represent an image. For Color feature extraction, techniques like Color histogram (CH), Color Moment (CM) have been described. Grey level co-occurrence matrix (GLCM) is used for texture features extraction. In this paper, fusion of Color and Texture based retrieval system is described. By using the fusion approach, better results can be produced with the higher precision value. Retrieval time of images is more so we design a CBIR system using many distance metrics for similarity calculation and by using the best distance metric for reducing the Retrieval time. Euclidean distance, KL-Divergence distance, Manhattan distance, Jaccard, Cosine distance is used. GLCM technique which is used for texture features extraction obtained 91% average precision, LBP features obtained 92% average precision and fusion of both texture features extraction obtained 95% average precision.*

Keyword:- *Color Histogram, Color Moment, Gray level co-occurrence matrix (GLCM), Content Based Image Retrieval System (CBIRS), LBP (local binary pattern).*

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1. INTRODUCTION

Since last few decades, systems working with retrieving large amount of multimedia data have been growing rapidly. Systems such as search engines, e-business systems, online tutoring system, GIS, and image archive are among few to them. Images are naturally endowed with attributes or information content that can help in resolving the image retrieval problem. The information content that can be derived from an image is classified into three levels. Low level – They include visual features such as color, texture, shape, spatial information and motion. Middle level – Examples include presence or arrangement of specific types of objects, roles and scenes. High level – Include impressions, emotions, and meaning associated with the combination of perceptual features. Finding similar images is indeed a challenging task from thousands of images is involved

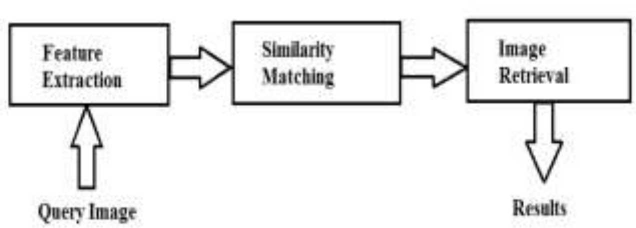

Figure 1.1: Basic concept of CBIRS

. In literature the term content based image retrieval (CBIR) has been used for the first time by Kato, to describe his experiments into automatic retrieval of images from a database by color and shape feature [2].Primary techniques did not generally depend on visual features; it was started with textual annotation of images. In alternative words, as query images were initially annotated with keywords and the then searching process is initiated by using a text-based approach from traditional database management systems. Through descriptions for the text or keywords, images can be managed by semantic or topical hierarchies to make a simple navigation and browsing which is based on standard Boolean queries. A CBIR system uses visual contents of the images described in the form of low level features like color, texture, shape and spatial locations to represent the images in the databases. The system retrieves similar images when an example image or sketch is presented as input to the system. The retrieval process is initiated when a user query the system using an example image or sketch of the object. The query image is converted into the internal representation of feature vector using the same feature extraction routine that was used for building the feature database. The similarity measure is employed to calculate the distance between the feature vectors of query image and those of the target images in the feature database. Finally, the retrieval is performed using an indexing scheme which facilitates the efficient searching of the image database.

2. RELATED WORK

In this paper, **T. Karthikeyan 2014** introduced TBIRS and CBIRS. Text-Based image retrieval has some disadvantages like; the task of decided image content is hugely perspective. So to control this problem, CBIRS was introduced. CBIRS is a rapidly growing technology with distinguished potential. In this paper, the focus is on the study of future enhancement and to implement the CBIRS in medical field [8]. Two new features for FIRE (Flexible Image Retrieval Engine) were executed that allows to retrieve images depending on Meta information and textual annotations and this new approach is introduced by **T. Deselaers 2004**. The text feature produces a connection between FIRE and a TBIRS. Now, an image database can be fined by using textual annotations of images. The user can either enter a query text into the web interface of FIRE or do a search that is only based on text retrieval or the user can provide an image with textual annotations and start normal image retrieval with text support [9]. In this paper, some fundamental theories of CBIRS were introduced by **Dr. Fuhui Long 2003**. The detailed evolution of TBIRS and CBIRS was discussed. Prior work on image retrieval can be discovered back in the 1970s. This time image retrieval is based on completed text annotations. In 1992, requirement generated the driving push behind the emergence of CBIRS techniques. And also for retrieval by the image is introduced. This evolution dates from the 1970s to 1997 in this paper [2]. In this paper, **Arnold W.M. Smeulders 2000** presented a view on: the driving force of the domain, the heritage from computer vision, the influence on computer vision, the role of similarity and of interaction, the need for databases, the problem of evaluation, and the role of the semantic gap [10]. In this article, **Remco C. Veltkamp 2001** gives a framework to present and compare CBIRS. Sixteen current systems are mooted in full information, in terms of querying, relevance feedback, result presentation, features, and matching. Basically, an overview of CBIRS has been discussed [12].

3. FEATURES EXTRACTIONS

The process of finding the expressive representation is known as feature extraction and the resulting representation is called the feature vector. Feature extraction can be defined as the act of mapping the image from image space to the feature space. Now days, finding good features that well represent an image is still a difficult task. Features usually represent the visual content. Low-level image feature extraction is the foundation of CBIR systems. Low-level features (color, texture, shape and spatial location).

3.1 EXTRACTING COLOR

One of the most significant features of image that make possible the recognition of images by humans is color [9].

3.1.1 Color Histogram

By quantizing the colors within the image and counting the number of pixels of each color, the color histogram for an image is constructed. In more detail, we can say that, given a color space (e.g. YUV), an image can be projected onto three color channels (Y, U, and V). So, an image can be divided into three color components, each of these components can be regarded as a gray level image under some color channel. Then, from the histograms of its color components, the feature vector of an image can be derived. Before, generating a histogram for a gray-level image, the bin number of the histogram, N, must be given in advance; such that each pixel in the image is grouped into the bin whose center is the nearest to the value of the pixel. Then, these numbers of pixels in the bin gives the value of the bar in the histogram.

$$D_{Histo}\,(Q, I) = \frac{\sum_i |D_{Histo\ i} - I_{Histo\ i}|}{\sum_i D_{Histo\ i}} \tag{1}$$

3.1.2 Color Moments

Color moments are used to overcome the quantization effects of the color histogram, as fea ture vectors for image retrieval. Any color distribution can be characterized by its moments. Most information is concentrated on the loworder moments, only the first moment (mean), the second moment (variance) and the third moment (skewness) are taken as the feature vectors. Due to a very reasonable size of feature vector, the computation is not expensive. However, the basic concept behind color moments lays in the supposition that the distribution of color in an image can be interpreted as a probability distribution. Its advantage is that, its skewness can be used as a measure of the degree of asymmetry in the distribution [11].

Mean: $ui = \frac{1}{N}\sum_{j=1}^{N} pij$ (2)

Standard Deviation: $\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(pij - ui)}^{\;2}$ (3)

Skewness: $s_i = (\frac{1}{N}\sum_{j=i}^{n}(pij - ui)^{3})^{\frac{1}{3}}$ (4)

3.2 EXTRACTING TEXTURE

Texture is a main component of human visual perception. Like color, this also makes it an essential feature to consider when querying image databases.

3.2.1 Gray-level co-occurrence matrix (GLCM)

Gray Level Co-occurrence Matrix (GLCM) is one of the well accepted representations for the texture in images. It generally incorporates a count of the number of times a given feature (for example, a given gray level) exists in a particular spatial relation to another given feature. GLCM is one of the most popular texture analysis methods, estimate various image properties related to second-order statistics. The process involved is as follows: 1. First of all, co-occurrence matrices for the images in the database and also the query image are computed. For each image, four matrices will be generated. 2. Next step is to build up a 4×4 features from the previous co-occurrence matrices. Four main features used in feature extraction are energy, entropy, contrast and homogeneity The content of an image is defined using five characteristic such as contrast, energy, entropy, correlation, and local stationary. The characteristic is computed by considering all the four directions, i.e., (i) horizontal (0°), (ii) vertical (90°), (iii) diagonal: (a) bottom left to top right (−45°) and (b) top left to bottom right (−135°). These are denoted as P0, P45, P90, P270, and P135, respectively. The equations for identifying texture measures can be computed from gray-level co-occurrence matrices as shown below:

Mean = $\sum_i \sum_j P(i,j) * i$ (5)

Variance = $\sum_i \sum_j P(i,j) * (i - u^2)$ (6)

Homogeneity = $\sum_i \sum_j \frac{P(i,j)}{1+|i-j|}$ (7)

Contrast = $\sum_i \sum_j P(i,j) * (i-j)^2$ (8)

Entropy = $\sum_i \sum_j -P(i,j) * \log_e P(i,j)$ (9)

Angular Second Moment = $\sum_i \sum_j P(i,j)^2$ (10)

Correlation = $\sum_i \sum_j (i - u_x) * (j - u_y) * P(i,j)$ (11)

Dissimilarity = $\sum_i \sum_j \frac{1}{1+(i-j)^2} * P(i,j)$ (12)

3.2.2 Local Binary Pattern (LBP)

The proposed system also makes use of a simple LBP [19] to extract the texture of the image. This extraction algorithm is performed over the subset of images selected from the first level of the retrieval process. Before exploring LBP on the selected images, RGB to gray scale transformation is carried out as a pre-processing step on these images. For each iteration, it takes 3 × 3 overlapping gray scale image as input. The pixel value available in the Center Position (CP) of the 3 × 3 sub block acts as a threshold value for its neighboring pixels. Using this threshold value, binary representation of that sub block is created. Then, the LBP value of the 3 × 3 sub block is evaluated in the counter clockwise direction.

Equation shows the estimation of LBP [19] for a 3 × 3 block representation:

$$LBP_N = \sum_{i=0}^{N-1} f(P_i - CP)2^i \quad (13)$$

4. FUSION OF COLOR AND TEXTURE FEATURES

CBIRS is a searching technology which is used in databases by using image contents like color, texture. If we use one attribute, it is quite difficult to get the perfect outcome. Integration of color, texture and shape features brings better and effective results than all another system [7]. The steps for image re trieval are as follows: 1) Using different techniques for color and texture feature extraction is done. 2) Calculation of similarity based on any distance metric 3) after that, a fusion of each feature depending on linking algorithm to be used. 4) Evaluation of fusion-based results 5) finally, obtains evaluation metrics in the form of precision and recall [36].

4.1 VARIOUS DISTANCE METRIC

The degree of similarity between query and target images is calculated based on the value of similarity measure. The images are ranked according to their similarity value and presented as output of CBIR system. Often, the choice of similarity measure affects the performance of retrieval system. Many similarity measures have been developed over the years based on the quantitative estimates of the distribution of features in the image.

4.4.1 Kullback–Leibler distance (KL—distance)

KL Divergence, which is also referred as Kullback–Leibler distance (KL—distance) can be applied, which acts as a natural distance function from an "exact" probability distribution, p, to "required" probability distribution q.

$$KL(p,q) = \sum_i pi.\log_2(\frac{p_i}{q_i}) \quad (14)$$

4.4.2 Euclidean distance

The most popular and widely used similarity measure in image retrieval is Euclidean and is given by [30]:

$$D_E = \sqrt{\sum_{i=1}^{n}(|I_i - D_i)^2|} \quad (15)$$

4.4.3 Manhattan Distance

This method also called by the name of city block distance and is expressed by the following given equation [30]:

$$D_C = \sum_{i=1}^{n}|I_i - D_i| \quad (16)$$

4.4.4 Jaccard

One minus the Jaccard coefficient, which is the percentage of nonzero coordinates that differ is given as:

$$d_{st} = \frac{\#[(x_{sj} \neq x_{tj}) \cap ((x_{sj} \neq 0) \cup (x_{ij} \neq 0))]}{\#[(x_{sj} \neq 0) \cup (x_{tj} \neq 0)]} \quad (17)$$

4.4.5 Cosine Distance

$$CAD\ (X,Y) = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2}\sqrt{\sum_i y_i^2}} \quad (18)$$

$$CAD\ (X,Y) = \frac{X.Y}{\|x\|\|Y\|} \quad (19)$$

One important property of vector cosine angle is that it gives a metric of similarity between two vectors unlike Euclidean distance, which give metrics of dissimilarities.

5. PERFORMANCE EVALUATION

To examine the performance of image retrieval systems two major evaluation metrics, Precision is used.

1)Precision :

Precision or Confidence denotes the proportion of Predicted Positive cases that are correctly Real Positives [40].

$$\text{Precision: } P = \frac{\textit{Number of relevant images retrieved}}{\textit{Total number of images retrieved}} \quad (20)$$

Table 5.1: Average Precision for GLCM, LBP and for proposed approach

Approach	Precision%
GLCM-CBIRS	91
LBP-CBIRS	92
Proposed (GLCM+LBP-CBIRS)	**95**

GLCM technique which is used for texture features extraction obtained 91% average precision, LBP which is used to extract color features obtained 92% average precision and fusion of both texture features extraction obtained 95% average precision.

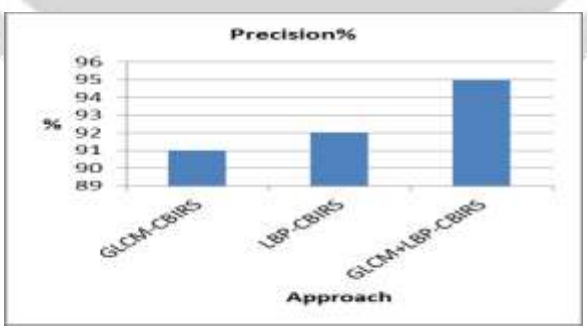

Figure 5.1 Average Precision Representations for GLCM, LBP and Fusion of Both

Table 5.2: Representation of average precision for various distance matrices

Distance Metric	Precision%	Time Complexity(second)
Euclidean	95	123.629625
Kldiv	86	61.731774
manhattan	**95**	**10.750423**
Cosine	95	193.928593
Jaccard	67	116.012137

The average precision has been calculated for all distance Metrics and this precision is averaged after getting average outcomes from all categories. Manhattan distance computed higher precision compare to other distance metrics.

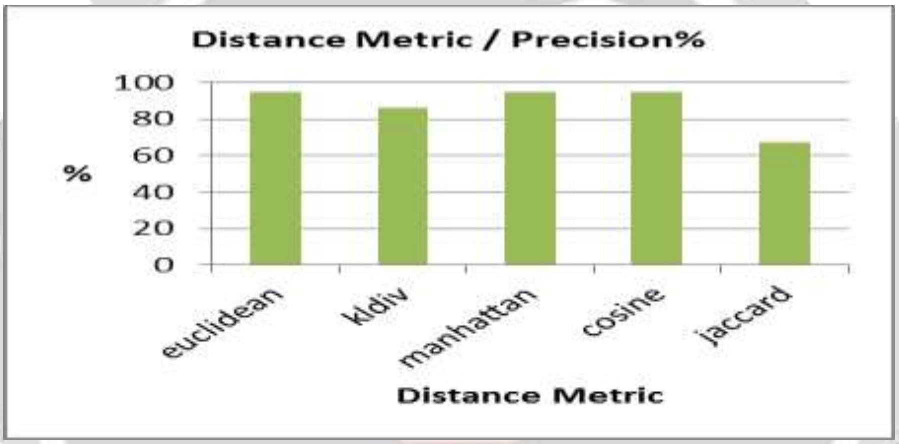

Figure 5.2: Bar graph Representation of all distance metrics with calculated average precision

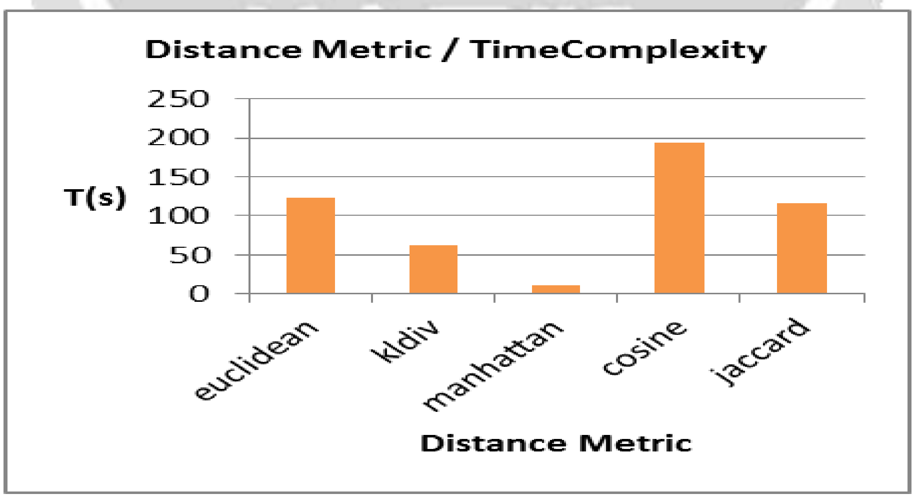

Figure 5.3: Bar graph Representation of all distance metrics with calculated average Time (s)

In this graph, the average time has been calculated for all distance matrices and this time is averaged after getting average outcomes for time from all categories. Manhattan distance computed lesser time compare to other distance metrics for features extraction.

CONCLUSION

A new hybrid feature scheme is proposed for efficient CBIR in this thesis based on color and texture with various distance metrics. The main benefaction of this work is to construct an efficient (well organized) and effective (productive) CBIR system that tends to be workable for massive datasets. Therefore, this proposed work has presented an efficient image indexing and search system based on color and texture features. The color features are described by fused histogram and statistical moments and texture features are described by a gray level co-occurrence matrix (GLCM). A group of experiments was executed to select the optimum vocabulary size that obtains the best retrieval performance. All considered retrieval procedures are analyzed on Wang datasets in RGB color spaces. The evaluation is carried out using the standard Precision. The outcomes present that our proposed approach produces better results. The proposed approach is effective in image retrieval. Six distance metrics (Euclidean Distance, KL divergence Distance, Cosine Distance, Manhattan Distance, Jaccard Distance are compared to check the better results. And among them, KL divergence distance provides the best outcomes. GLCM technique which is used for texture features extraction obtained 91% average precision, LBP which is used to extract color features obtained 92% average precision and fusion of both texture features extraction obtained 95% average precision.

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