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Image Clustering and Retrieval using LTCoP Similarity Measures

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Abstract

The purpose of content based image retrieval (CBIR) systems is to allow users to retrieve images from large image repositories. In a CBIR system, an image is usually represented as a set of low level descriptors from which a series of underlying similarity measures are used to conveniently drive the different types of queries. In this paper, feature extraction and different similarity measures are used for Image retrieval. This work proposed a novel feature extraction algorithm called local ternary co-occurrence patterns (LTCoP) for biomedical image retrieval. The LTCoP encodes the co-occurrence of similar ternary edges which are calculated based on the gray values of center pixel and its surrounding neighbours. Whereas the standard local derivative pattern (LDP) encodes the co-occurrence between the first-order derivatives in a specific direction. In addition, the effectiveness of our algorithm is confirmed by combining it with the Gabor transform. After feature extraction, compare the query image with the images in the database using similarity measure. The proposed method is extensively tested on Corel datasets with 150natural images. The results demonstrate that it is much more efficient and effective than representative feature descriptors of state of art based image retrieval.

Keywords: similarity measure, similarity distance, image retrieval, feature extraction.

1. INTRODUCTION

1.1 OVERVIEW

In recent years, as technology develops we gets collections of images and videos. So, content-based retrieval and querying the indexed collections are required to access visual information. As a powerful technique, content-based retrieval systems have to provide easy-to-index data structures as well as faster query execution facilities. The users pose to seek visual information, the content of the images and videos in order to extract. The images and video frames can be categorized as follows: spatial, semantic, and low-level. Since video data has a time dimension, the spatio-temporal content of a video data is also considered. However, extracting spatio-temporal content requires intellectual techniques for categorization. The spatial content of an image is the relative positioning of the objects residing in the image. The semantic content is the actual meaning of the image that a user captures when he/she looks at the image. The low-level content is formed by low-level features such as color, shape, and texture. These three features are considered important fundamental primitives in human visual perceptions of the real world. Various methods exist in the literature for indexing the images based on these low-level features.

A wide variety of models have been considered for image retrieval from the very simple early vision techniques, like similarity measures to very sophisticated methods, applicable for specific and restricted environments. In the past, the scientific community propagated three types of content based image retrieval approaches: semi-automatic extraction of attributes, automatic feature extraction and object recognition, Semi-automatic systems provide tools to accelerate the annotation process; however, they require manual interaction for database generation. The user might manually segment objects in the image, followed by an automatic analysis and annotation by the computer. Such systems considerably accelerate the image annotation. Semi-automatic systems can only work off line, i.e., a database has to be generated before queries can be provided. Hence, they are not well suited for heavily fluctuating data like for example a collection of Internet sites. In addition these systems are limited in size due to the fact that new image data might be faster acquired than manual annotations can be added.

Fully automatic systems overcome these problems since the analysis can be done at query time, if the data set has not been analyzed before. Nonetheless, for unrestricted image retrieval problems, there is a large gap between objective image features, that have been extracted, and the semantics of an image. A necessary pre-requisite of features is invariance; no matter whether they are local, global or semantic. Invariant features remain unchanged in case the image content is transformed according to a group action, i.e. the features obtained for an unaltered or from a transformed image are mapped to the same point in feature space. A simple example is the similarity measures of an image that remains identical under any permutation of the image pixels. The invariance property might simplify the comparison of images. Clearly, does the invariance property average an object's content in terms of feature space representation. Therefore, each invariant feature should be able to describe various transformations of an object, while remaining a unique descriptor. Hence, we will evaluate the invariance properties of the proposed structure-based features and the consequences of retrieving similar images.

1.2 CONTENT BASED IMAGE RETRIVAL

Content Based Image Retrieval (CBIR) technique uses image content to search and retrieve digital images. This system are introduced to address the problems associated with text-based image retrieval. Content based image retrieval is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features The main objective of CBIR is efficient during image indexing and retrieval, thereby, human intervention in the indexing process is reduced.

The similarity comparison is one of the main tasks for CBIR systems. Extracting feature signatures of every image based on its pixel values and defining rules for comparing images. These features become the image representation for measuring similarity with other images in the database.

1.2.1 IMAGE RETRIEVAL PROBLEM

A large collection of images is referred to as image database. An image database is a system where image data are integrated and stored. Image data include the raw images and information extracted from images by automated or computer assisted image analysis.

1.2.2 FIELDS OF APPLICATION

Image retrieval based on content is extremely useful in a plethora of applications such as publishing and advertising, historical research, fashion and graphic design, architectural and engineering design, crime prevention, medical diagnosis, geographical information and remote sensing systems, etc.. A typical image retrieval application example is a design engineer who needs to search his organization database for design projects similar to that required by his clients, or the police seeking to confirm the face of a suspected criminal among faces in the database of renowned criminals. The most important application, however, is the Web, as big fraction of it is devoted to images, and searching for a specific image is indeed a daunting task. Numerous commercial and experimental CBIR systems are now available, and many web search engines are now equipped with CBIR facilities, as for example Alta Vista, Yahoo and Google.

1.2.3 PRINCIPLE OF CBIR

Content-based retrieval uses the contents of images to represent and access the images. A typical content-based retrieval system is divided into off-line feature extraction and online image retrieval. In off-line stage, the system automatically extracts visual attributes (color, shape, texture, and spatial information) of each image in the database based on its pixel values and stores them in a different database within the system called a feature database. The feature data) for each of the visual attributes of each image is very much smaller in size compared to the image data, thus the feature database contains an abstraction of the images in the image database.

In on-line image retrieval, the user can submit a query example to the retrieval system in search of desired images. The system represents this example with a feature vector. The distances between the feature vectors of the query example and those of the media in the feature database are then computed and ranked. Retrieval is conducted by applying an indexing scheme to provide an efficient way of searching the image database. Finally, the system ranks the search results and then returns the results that are most similar to the query examples. If the user is not satisfied with the search results, he can provide relevance feedback to the retrieval system, which contains a mechanism to learn the user's information needs.

1.2.4 SIMILARITY MEASURE

The similarity between two images (represented by their feature values) is defined by a similarity measure. Selection of similarity metrics has a direct impact on the performance of content-based image retrieval. The kind of feature vectors selected determines the kind of measurement that will be used to compare their similarity. If the features extracted from the images are presented as multi-dimensional points, the distances between corresponding multi-dimensional points can be calculated. Euclidean distance is the most common metric used to measure the distance between two points in multi-dimensional space

1.2.5 PERFORMANCE EVALUATION

The performance of a retrieval system is evaluated based on several criteria. Some of the commonly used performance measures are average precision, average recall, average retrieval rate and Average Normalized modified Retrieval Rate (ANMRR). All these parameter are computed using precision and recall values computed for each query image. The precision of the retrieval is defined as the fraction of the retrieved images that are indeed relevant for the query:

$$Precision = \frac{\text{No of relevant images retrieved}}{\text{Total no. of images retrieved from the database}}$$

The recall is the fraction of relevant images that is returned by the query:

$$\text{Recall} = \frac{\text{No. of relevant images retrieved}}{\text{Total no. of relevant images in the data base}}$$

A good retrieval system should have high values for precision and recall.

DIGITAL IMAGE

A digital image can be considered as a matrix whose row and column indices identify a point in the image and the corresponding matrix element values identifies the gray level at that point. In a most generalized way, a digital image is an array of numbers depicting spatial distribution of a certain field of parameters. Digital image consists of discrete picture elements called pixels. Based on the way that image data is saved, images can be split into 3 different types: bitmap, vector and metafile.

BITMAP

Bitmaps images are exactly what their name says they are: a collection of bits that form an image. The image consists of a matrix of individual dots (or pixels) that all have their own color described using bits. Bitmap graphics are also called raster images**.** A picture saved using the Paint program is likely to have the .bmp file extension, for bit map. The data in .bmp files is not compressed; therefore bitmap files tend to be very large. Bitmap graphics can be saved in any of these formats: GIF, JPEG, TIFF, BMP, PICT, PNG and PCX.

VECTOR

In vector graphics, the co-ordinates of images (lines and curves) are saved as mathematical data. You can imagine the co-ordinates as being all the points through which lines or curves pass. It's a little like drawing a square on a piece of graph paper and describing it, using the co-ordinates of all 4 corners. Computer Aided Design (CAD) is based on vector graphics. Images produced using vector graphics are ideal for many purposes because they're so much smaller than bitmaps - it is not necessary to store information about every pixel, just about the lines and curves, their co-ordinates, width and color.

META FILE

Metafile graphics are basically 2D graphics that are made up of both vector and bitmap**.** If you drew a shape using vector graphics, and then filled it with a bitmap pattern, then you would have metafile. The vector object still retains the property of scalability without any loss of resolution. The circle above was created as a vector graphic, and then a fill added. It was saved as a .gif to include on this page, which unfortunately changes it to a bitmap with a subsequent loss of scalability. .

DIGITAL IMAGE PROCESSING

Image processing deals with the processing and display of images of real objects. Their emphasis is on the modification of the image, which takes in a digital image and produces some other information, decision etc.

A digital image is an array of real or complex processing of any two dimensional data.

1. Each point (x, y) has an intensity value, or color.
2. Not All Images are Equal.
3. Images can be manipulated to extract desired information.
4. Best end result a matter of taste.

The elements of the general-purpose system capable of performing the image processing operations are

1. Image Acquisition
2. Image Storage
3. Processing the image
4. Communication
5. Display

Storage of digital processing elements falls in the following three categories. They are

1. Short-term storage - used during processing
2. Online storage - for relatively fast recall
3. Archival storage - characterized by infrequent access

Processing of digital image involves procedures that are usually expressed in algorithmic form. The exception of image acquisition and display, most image processing functions implemented in software. Monochrome and color TV monitors are the principle display devices used in modern digital processing systems. Printing image display devices are useful primarily for low-resolution image processing work.

1.4 OBJECTIVE OF WORK

The aim of this paper is to propose a new CBIR system; an important task of the system is 1) to reduce the "semantic gap" between low-level image features and the richness of human semantics and 2) to reduce the overall retrieval time. The goal is to present the user with a subset of images that are more similar to the query image. New LTCOP feature extraction techniques are proposed to improve retrieval performance and reduce the extraction and search times. The techniques are tested both generally for multi-component images and particularly for any pictures. The solutions are discussed for each specific application. Finally, content-based image retrieval, which explores image retrieval from databases using different distance metrics, is investigated on an individual basis.

This paper is devoted to improving existing techniques involved in feature extraction, clustering and reducing the overall computation time of image retrieval system while increasing the accuracy. The main contributions of the paper are listed below:

1. Design and development of a multistage similarity measurement model for image retrieval to improve the retrieval accuracy by filtering down irrelevant images at each stage.
2. The structural and statistical approaches of texture description are utilized to develop a single feature which can thoroughly describe the correlation between color and texture properties of image.
3. Even though CBIR systems increased the retrieval accuracy, they require high complex computations to calculate similarity, since these systems need to consider each region in the database images, resulting in high retrieval response time. Thus, we need a solution to reduce the number of database regions included in the similarity computation
4. The LTCoP is robust to the different lighting conditions as compared to LBP and LDP
5. The performance of the proposed method is confirmed by combining it with the Gabor transform.
6. The performance of the proposed method is analyzed with the difference distance measures.

2. BACKGROUND WORKS

Background Works is an analysis on gathered information about the topic, which in this context, the system which we intend to develops. In order to gauge the state or limitation of existing system, this approach will be use in evaluation of existing system with regards to the topic. And hopefully, the evaluation results would provide basis on factors that could be improves or develops upon.

Guang-Hai Liu and Zuo-Yong Li propose a novel feature detector and descriptor, namely microstructures descriptors (MSD), to describe image features via Micro structures.[1]

The micro structures are defined by computing edge orientation similarity and the underlying colors, which can effectively represent image local features. The underlying colors refer to those colors that have similar edge orientation, and they can mimic human color perception well. With micro structures serving as a bridge, the MSD can extract and describe color, texture and shape features simultaneously. The MSD has advantages of both statistical and structural texture description approaches. In addition, the MSD algorithm simulates human visual perception mechanism to some extent. The main advantages are High indexing performance and low dimensionality and Use visual perception mechanism for image retrieval. But in this method some relevant information is suppressed.

In CBIR, a relevance feedback-based approach allows a user to interact with the retrieval algorithm by providing the information of which images he or she thinks are relevant to the query Based on user feedback, the model of similarity measure is dynamically updated to give a better approximation of the perception subjectivity.

Yixin Chen and Robert Krovetz works that combine relevance feedback with supervised learning Binary classifiers are trained on the fly based on user feedback. Empirical results demonstrate the effectiveness of relevance feedback for certain applications.[2] Nonetheless, such a system may add burden to a user especially when more information is required than just Boolean feedback (relevant or non relevant). Statistical classification methods group images into semantically meaningful categories using low-level visual features so that semantically adaptive searching methods applicable to each category can be applied For example, the SemQuery system categorizes images into different set of clusters based on their heterogeneous features. Vacation images into a hierarchical structure.

Wei Jiang and Qionghai Dai deals the online learning process.[3] It must tackle a fundamental problem: which features are more representative for explaining the current query concept than the others. This refers to the problem of online feature selection, which is the issue they mainly address in this work. Compared with other machine learning problems, CBIR online learning has three challenges. 1) Small size of the training set: The training samples are the labeled images from the user during each query session, which are very few compared with the feature dimensionality and the size of the database. The CBIR learning algorithm usually encounters severe problems due to the curse of dimensionality. 2) Intrinsic asymmetry: The images labeled to be “relevant” during a query session share some common semantic cues, while the “irrelevant” images are different from the “relevant” ones in different ways. Thus, the “relevant” images are more important for the system to grasp the query concept. This asymmetry requirement makes it necessary to treat the “relevant” and “irrelevant” sets unequally with an emphasis on the “relevant” one. 3) Fast response requirement: The system should give out the retrieval results within a tolerable amount of time.

Due to the above three special requirements, most classical feature selection criterions, such as the distribution based approaches [e.g., mutual information maximization (MMI) method and Kullback Leibler divergence (K–LD) method and the conventional boosting approach are not suitable for CBIR online learning. Since the few training samples are usually not representative of the whole dataset, it is difficult for the system to well estimate the samples’ distribution. For the same reason, the conventional boosting method will not perform well because of the poor generalization ability due to the training-error-based feature selection criterion. Furthermore, the asymmetry requirement is not considered in these feature selection methods. There is another kind of methods for online feature selection in CBIR, which is called the discriminant analysis (DA) approach. Multiple discriminant analysis (MDA) method biased discriminant analysis(BDA) method and symmetric maximized minimal distance in subspace (SMMS) method are three typical approaches. They generalize linear discriminant analysis (LDA) and assume that the “relevant” images group together as one cluster. To meet the asymmetry requirement they do not assume the one cluster distribution for “irrelevant” images. MDA assumes that each “irrelevant” image is from a different class, while BDA assumes that the “irrelevant” images come from an uncertain number of classes. From the aspect of computation, MDA and BDA minimize the covariance of the “relevant” set (the within class scatter S_W) over the between class distance (the between class scatter S_B). SMMS selects the feature subspace which is perpendicular to the subspace spanned by the “relevant” samples. This method achieve a high detection rate. The limitations are computational complexity and training error due to high dimensionality.

Minh N. Do and Martin Vetterli consider a simple architecture of a typical CBIR system where there are two major tasks.[4] The first one is feature extraction (FE), where a set of features, called image signatures, is generated to accurately represent the content of each image in the database. A signature is much smaller in size than the original image, typically on the order of hundreds of elements (rather than millions). The second task is similarity measurement (SM), where a distance between the query image and each image in the database using their signatures is computed so that the top “closest” images can be retrieved. Typically, the features used in CBIR systems are low-level image features such as color, texture, shape and layout. In this work, they focus on then use of texture information for image retrieval.

It is a challenging task to find good similarity measures between images based on some feature set. The ultimate goal is to define similarity functions that match with human perception. As per the perceptual studies it identifies texture dimensions by conducting experiments which observers intents to group textures according to perceived similarity. The detected perceptual criteria and rules for similarity judgment from this type of subjective experiments can be used in building image retrieval system. Many current retrieval systems take a simple approach by using typically norm-based distances. The main premise behind these CBIR systems is "good set" of features extracted from the images in the database. The extracted images are "similar" because the extracted features are "close" to each other. Therefore, any reasonable similarity functions can perform well. The weighting factors are used to normalize extracted features over the entire database to comparable ranges so that they have approximately the same influence on the overall distance.

In this work the problems of FE and SM in texture retrieval is used as a statistical approach. The low level representation, statistical modeling provides a natural mean to formulate the retrieval problem, as it is typically done in pattern recognition. The implication of this approach is twofold. First, it provides a confidence on the optimality of the defined similarity function under some explicit assumptions. Secondly, this approach provides a common ground for many existing similarity functions by simply modifying the underlying assumptions. Statistical modeling has been used in CBIR systems before. The most well-known examples are the use of histograms to capture the distribution of image features such as color. This work has greater accuracy and flexibility in capturing texture information also good set of extracted features but also together with a suitable similarity measurement.

During 1990s fuzzy logic based approaches were brought in image retrieval. Fuzzy histogram analysis helped to include ambiguity and vagueness in perceiving color or texture A number of similarity measures for these fuzzy histograms were also defined.In 2003 Ralescu proposed fuzzified version of the existing hamming distance measure using color as feature. It provides a fuzzy distance measure between non fuzzy real valued vectors. Thus without fuzzification of existing feature vectors, the ambiguity in their similarity is identified. Ionescu in his work used Fuzzy Hamming Distance (FHD) to find similarity between color Histogram.

Sreena P. H. and David Solomon George gives general overview of a CBIR system. [5] The first step in developing a CBIR system is feature database creation. The feature database should contain feature vector corresponding to each image in the database. A feature vector is selected depending on the nature of database and application of the system. On presenting a query image to the system, its feature vector is extracted and similarity/distance with all feature vectors in database is measured. Images with largest similarity or shortest distance are made available to the user after sorting. 2013 International Conference on Control Communication and Computing (ICCC)

In this work a CBIR system which extracts texture features from images and compares it with that of database images is proposed. A statistical texture measurement called Tamura texture of the standard Bordatz database is extracted. Fuzzy modification of hamming distance, Fuzzy Hamming Distance, is used for comparison of the images. The system sorts the database in the increasing order of comparison result, i.e., the distance measure between query image and database images. The images with lowest distance measure are the most similar images. The advantages of this work is **f**eature has got multiple representations. But difficult in visual perception mechanism and retrieved images are irrelevant.

Overall issues of Existing system :

- Hard to obtain automatic annotation of large set of images.
- Lower performance in image retrieval recognition rate.
- Lower efficiency over noise-induced variations.
- Huge computation overhead of quantization and search.
- Less retrieval accuracy and low speed.

3. PROBLEM DESCRIPTION

Texture is an innate property that describes visual pattern containing information about surface, fabric etc. Which relates the relationship of surface with the surroundings. Texture can be modelled as quasi per with spatial/frequency representation. It brings effective image search and retrieval. According to this transform a function that represent a image i.e. a curve signal, can be described in terms of coarse level description in addition to others details and range from narrow to broad scales.

In this paper, a new image indexing and retrieval algorithm is proposed using local ternary co-occurrence patterns (LTCoP). The LTCoP encodes the co-occurrence of similar ternary edges in an image.

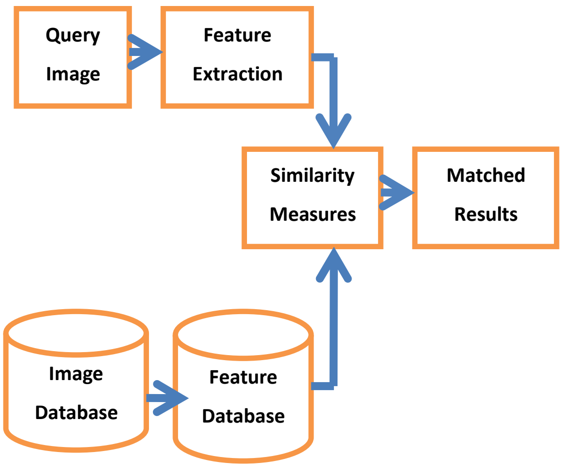

Fig 3.1: System Architecture

Feature vector F(V1)of LTCoP transform image :

Texture is an important characteristic in image analysis and classification, and has attracted a lot of attention during the past decades. Texture classification is an important topic in the research areas of computer vision and pattern recognition. The proposed LTCoP is defined based on the first-order derivatives in eight directions

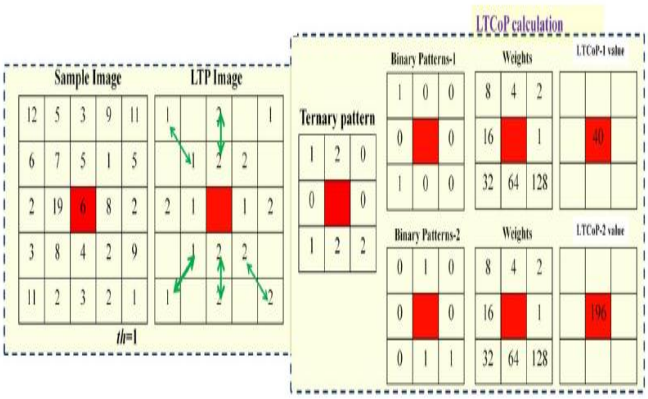

Fig 3.2: LTCoP based Feature extraction calculation

The center pixel (gc) are defined as follows:

$I_{PR}(g_i) = I_{PR}(g_i) - I_{P,R}(g_c)$; i=1,2,..................P

$I_{PR} + 1(g_i) = I_{P,R} +_1(gi) - I_{P,R}(g_i)$; i=1,2...............P

After calculation first-order derivatives, we code them based on the sign of derivative as follows:

$$I^1_{P,R}(g_i) = \tilde{\tilde{f}}_1(\tilde{I}_{P,R}(g_i))$$

$$I^1_{P,R+1}(g_i) = \tilde{\tilde{f}}_1(\tilde{I}_{P,R+1}(g_i))$$

The co-occurrence value calculation process for LTCoP is defined as follows:

$$LTCoP = \begin{bmatrix} f_3(I^1_{P,R}(g_1), I^1_{P,R+1}(g_1)), \\ f_3(I^1_{P,R}(g_2), I^1_{P,R+1}(g_2)), ... \\ ...., f_3(I^1_{P,R}(g_P), I^1_{P,R+1}(g_P)) \end{bmatrix}$$

$$f_3(x,y) = \begin{cases} 1 & \text{if } x = y = 1 \\ 2 & \text{if } x = y = 2 \\ 0 & \text{else} \end{cases}$$

The limited model among P neighborhoods, 2^P groups of binary models are doable, ensuing in feature vector length of 2^P. . In arrange to decrease the computational cost the consistent models are used. . In this paper, those models which contain a smaller amount or equal amount of discontinuities in the globular binary depiction are referred to as the uniform models and left over models are non-uniform. Thus, the different uniform models for a specified inquiry image would be P(P−1)+2 but destitute of revolving invariant. The revolving invariant LTCoP models can be defined by all eight directional models to the similar bin of histogram.

After the transformation of the original image, the histogram image is represented as per Eq.

$$H_S(l) = \frac{1}{N_1 \times N_2} \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_4(PTN(j,k), l); \quad l \in [0, L-1]$$

$$f_4(x,y) = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{else} \end{cases}$$

where, L means the number of bins and N1 X N2 means the dimension of the experimental image.

Feature vector F(V2)of Gabor transform image :

Gabor is introduced for texture interpretation of data. Gabor filters are collection of wavelets, with each wavelet capturing energy at specific type and in the specific direction. This method provides localized description of frequency. It can be extracted from this group of energy distribution. The scale and orientation make Gabor filter useful for analysis, which designed to detect different frequencies and orientations. Gabor features can be calculated from each filtered image and resultant images are retrieved. Our model rely on the fact that input images are excepted as Query by example (QBE) and any combination of images. The low level features which we are using are mean, median and standard deviation of red, green and blue colours. The image of the Texture feature consist of homogeneity, correlation, contrast and energy. We also use edge features which include vertical, horizontal, 45 degree diagonal, 135 degree diagonal and then isotropic are added.

Gabor function can be defined by the occurrence of the sinusoid ω and the standard deviations σ_x *and* σ_y of the Gaussian envelope as follows:

$$\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{(-(1/2)(x^2/\sigma_x^2 + y^2/\sigma_y^2) + 2\pi j\omega x}$$

Gabor filter is the complexity of Gabor casement with image I, and is given by

$$G_{mn}(x,y) = \sum_j \sum_t I((x-s, y-t)\psi^*_{mn}(s,t)$$

Gabor orientation process is applied to the original image then you will get Gabor transform image, the partioning process is applied to the Gabor transform image , then block count value is calculated for each intensity value (1-255) of Gabor orientation image. Finally the feature vector F(V2) is defined using Gabor filter orientation image.

Similarity measure :

Feature vector of query image Q is represented as $f_Q=(f_{Q1}, f_{Q2}........f_{QLg})$ obtained after the feature extraction. Similarly each image in the database is represented with feature vector $f_{DBj}= (f_{DBj1}, f_{DBj2}....... f_{DBjLg})$. The goal is to select n best images that resemble the query image. This involves selection of n top matched images by measuring the distance between query image and image in the database In this work, four types of similarity distance metrics are used and these are shown below:

L_1 or Manhattan distance measure:

$$D(Q,DB) = \sum_{i=1}^{Lg} \left| f_{DB_{ji}} - f_{Q,i} \right|$$

Euclidean distance measure:

$$D(Q,DB) = \left(\sum_{i=1}^{Lg} (f_{DB_{ji}} - f_{Q,i})^2 \right)^{1/2}$$

Canberra distance measure:

$$D(Q,DB) = \sum_{i=1}^{Lg} \frac{|f_{DB_{ji}} - f_{Q,i}|}{|f_{DB_{ji}}| + |f_{Q,i}|}$$

d_1 distance measure:

$$D(Q,DB) = \sum_{i=1}^{Lg} \left| \frac{f_{DB_{ji}} - f_{Q,i}}{1 + f_{DB_{ji}} + f_{Q,i}} \right|$$

where $f_{DB_{ji}}$ is the ith feature of jth image in the database $|DB|$.

3.1 PROPOSED SYSTEM

In this paper, feature extraction and different similarity measures are used for Image retrieval. This work proposed a novel feature extraction algorithm called local ternary co-occurrence patterns (LTCoP) for biomedical image retrieval. The LTCoP encodes the co-occurrence of similar ternary edges which are calculated based on the gray values of centerpixel and its surrounding neighbors. Whereas the standard local derivative pattern (LDP) encodes the co-occurrence between the first-order derivatives in a specific direction. In addition, the effectiveness of our algorithm is confirmed by combining it with the Gabor transform. After feature extraction, compare the query image with the images in the database using similarity measure. The goal is to select n best images that resemble the query image. This involves selection of n top matched images by measuring the distance between query image and image in the database. In this paper, four types of similarity distance metrics are used (1) Manhattan distance (2) Euclidean distance (3) Canberra distance and (4) D_1 distance. The proposed algorithm has high indexing performance and low dimensionality.

3.1.1 Advantages of Proposed system

- Results are computed in terms of the average precision rate and average retrieval rate
- Improved in performance
- Better in rotation and scaling conditions
- Detected very accurately over the textural databases.
- Improve the efficiency of image search.

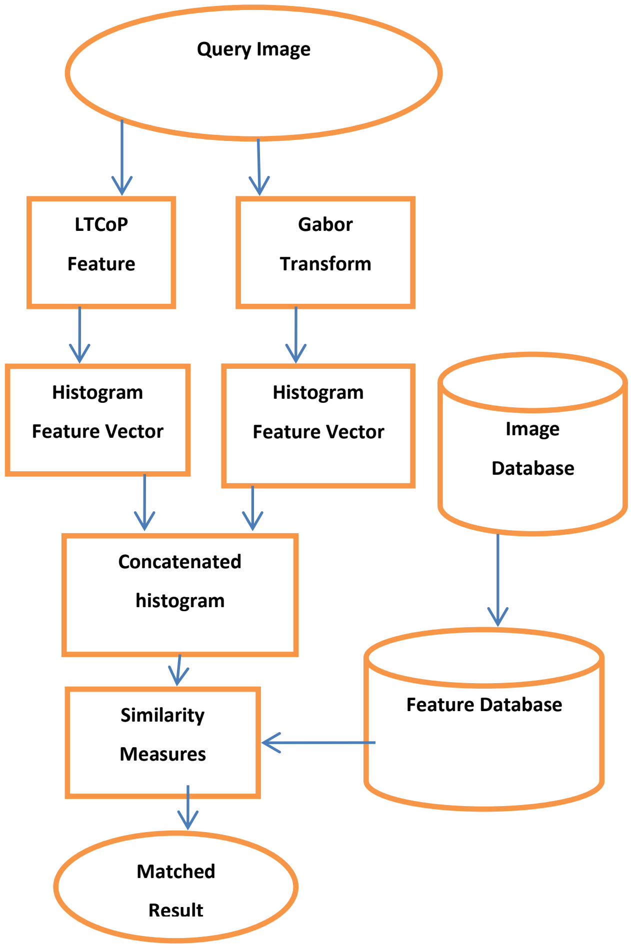

Fig 3.3: Image Retrieval Process

4. RESULT AND DISCUSSION

4.1 RESULT

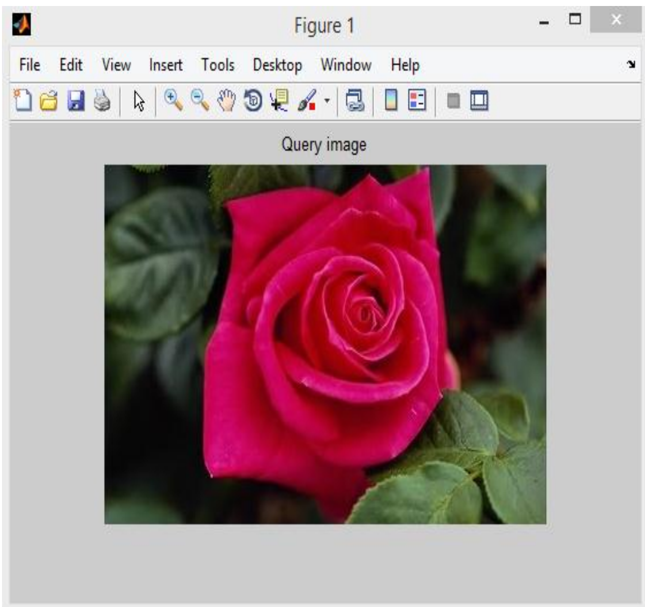

Fig 4.1: Query Image

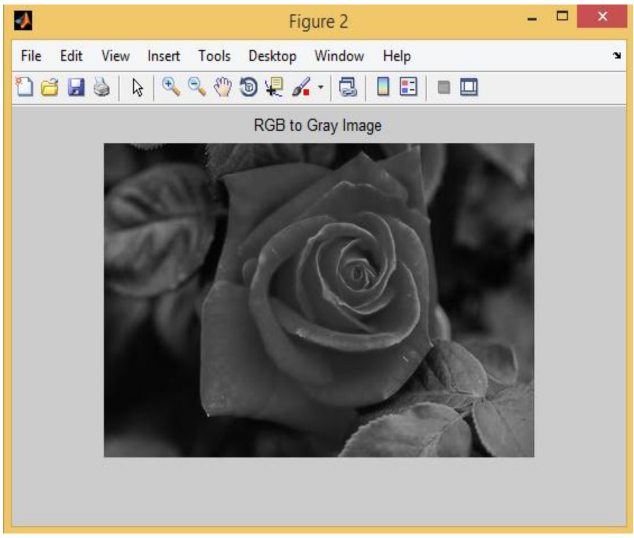

Fig 4.2: RGB to Gray Image

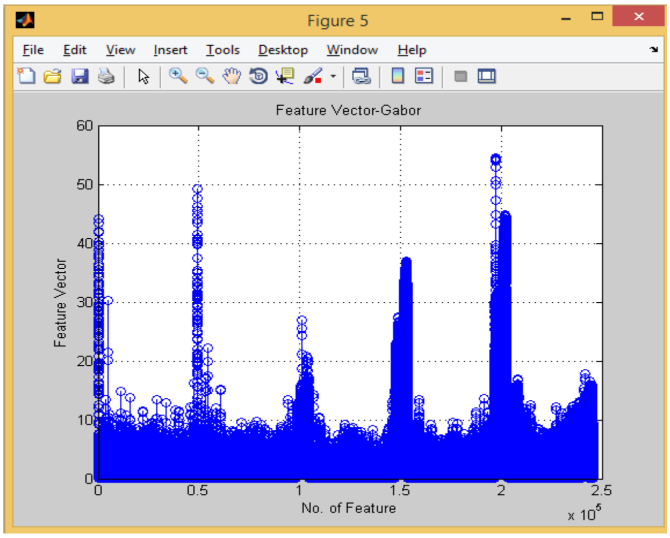

Fig 4.5: Feature Vector - Gabor

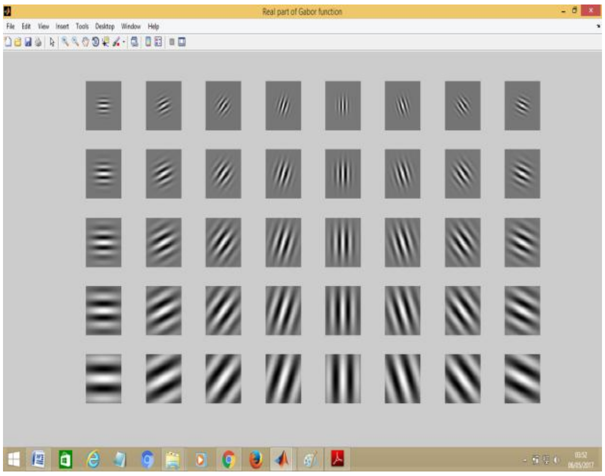

Fig 4.3: Real Part of Gabor Function

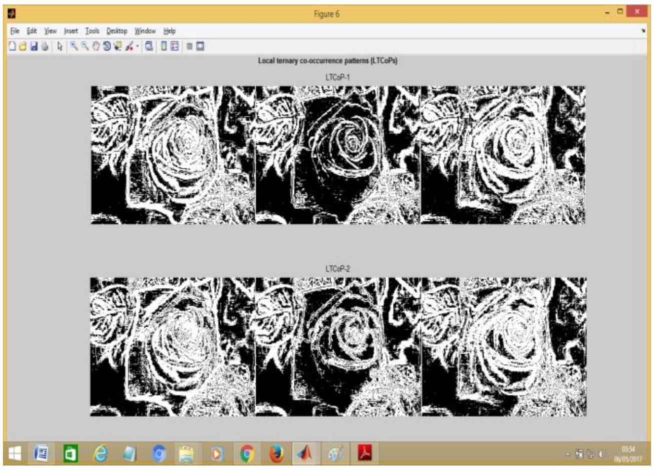

Fig 4.6: LTCoP Image

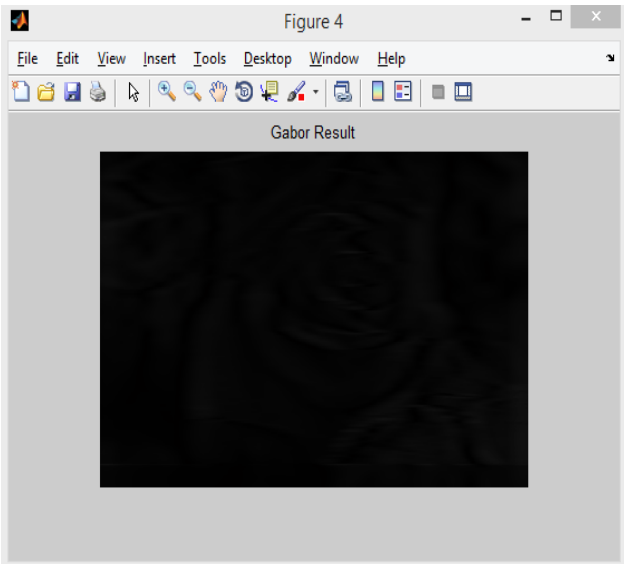

Fig 4.4: Gabor Result

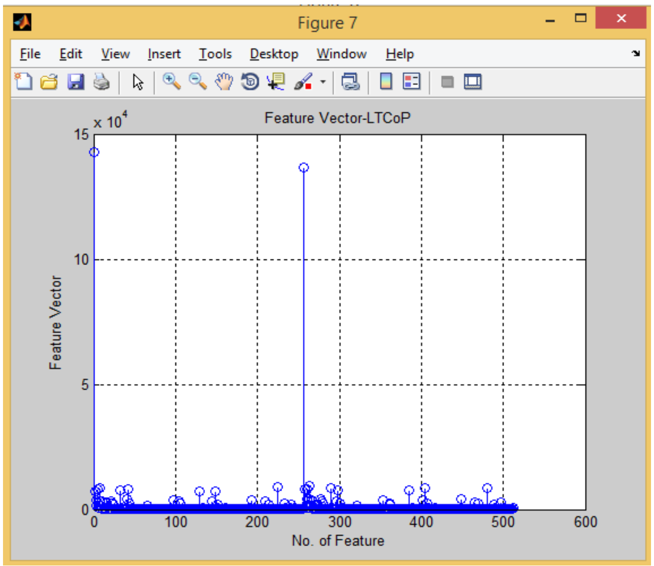

Fig 4.7: Feature Vector-LTCop

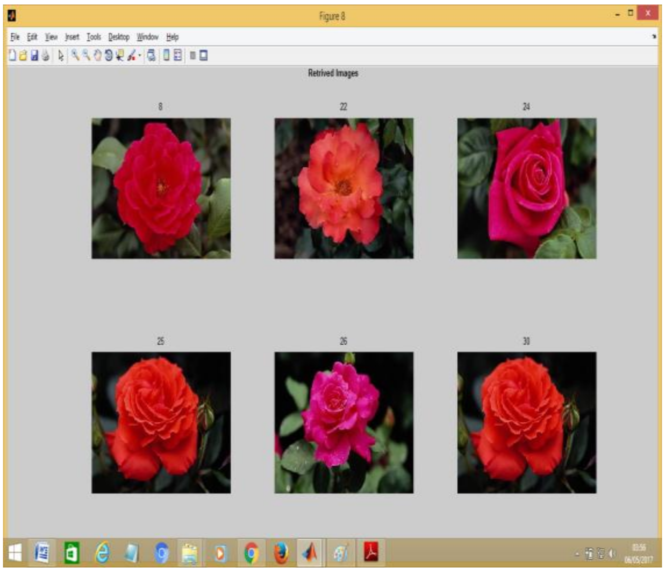

Fig 4.8: Retrieved Images

4.2 DISCUSSION

In this paper, conducted extensive CBIR experiments over databases containing the color images of natural scenes, textures, etc. The number of images, number of categories, number of images in each category and image resolutions used in the experiments. The images of a category of a particular database are semantically similar. For example, the Corel-1k database consists of 100 images from different categories namely „Buildings‟ , „Buses‟ , „Dinosaurs‟ etc. In the experiments, each image of the database is turned as the query image.

For each query image, the system retrieves top matching images from the database on the basis of the shortest similarity score measured using different distances between the query image and database images. If the returned image is from the category of the query image, then we say that the system has appropriately retrieved the target image, else, the system has failed to retrieve the target image.

The performances of different descriptors are investigated using ARP and ARR. To demonstrate the effectiveness of the proposed approach, we compared our results of Multichannel Adder and Decoder Local Binary Pattern (i.e. maLBP & mdLBP) with existing methods such as Local Binary Pattern (LBP). In content based image retrieval, the main task is to find most similar images of a query image in the whole database.

It used *Precision* and *Recall* curves to represent the effectiveness of proposed descriptor. For a particular database, the average retrieval precision (ARP) and average retrieval rate (ARR) are given as follows,

$$ARP = \frac{\sum_{i=1}^{\mathbb{C}} AP(i)}{\mathbb{C}} \quad \& \quad ARR = \frac{\sum_{i=1}^{\mathbb{C}} AR(i)}{\mathbb{C}}$$

where $\mathbb{C}$ is the total number of categories in that database, *AP* and *AR* are the average precision and average recall respectively for a particular category of that database and defined as follows for *i*th category,

$$AP(i) = \frac{\sum_{j=1}^{\mathbb{C}_i} Pr(j)}{\mathbb{C}_i} \;\&\; AR(i) = \frac{\sum_{j=1}^{\mathbb{C}_i} Re(j)}{\mathbb{C}_i} \;\forall\, i \in [1, \mathbb{C}]$$

where $\mathbb{C}\,i$ is the number of images in the *i*th category of that database, *Pr* and *Re* are the precision and recall for a query image and defined by the following equation

$$Pr(k) = \frac{NS}{NR} \;\;\&\;\; Re(k) = \frac{NS}{ND} \qquad \forall\, k \in [1, \mathbb{C}_j]$$

Where *NS* is the number of retrieved similar images, *NR* is the number of retrieved images, and *ND* is the number of similar images in the whole database.

4.2.1 Average retrieval Precision

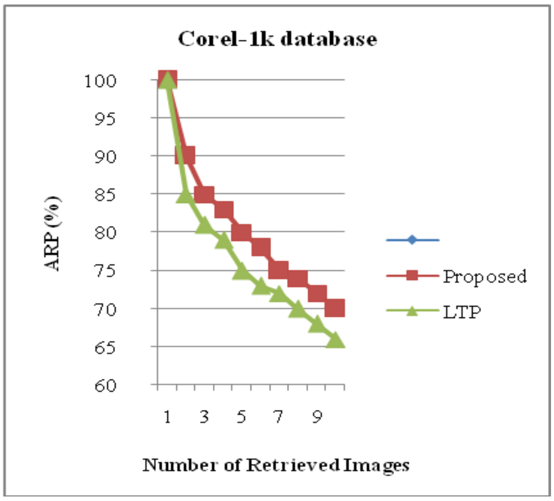

Fig 4.9: Average Retrieval Precision

Table 4.1: Average Retrieval Precision

Number of Retrieved Images	Proposed	LTP
1	100	100
2	90	85
3	85	81
4	83	79
5	80	75
6	78	73
7	75	72
8	74	70
9	72	68
10	70	66

4.2.2 Average retrieval rate

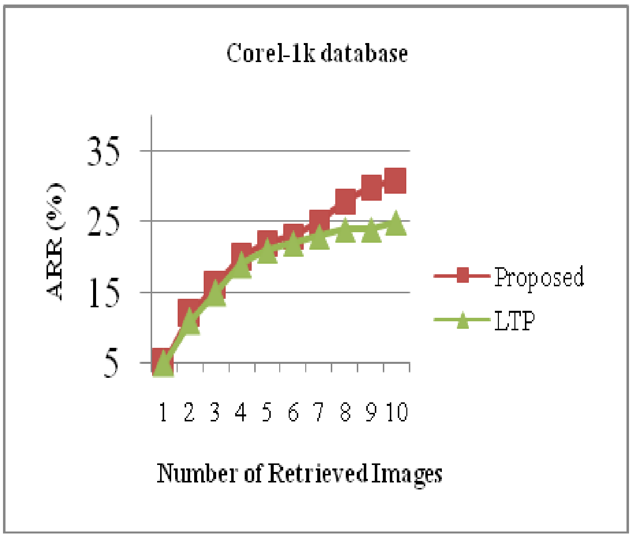

Fig 4.10: Average Retrieval Rate

Table 4.2: Average Retrieval Rate

Numbe of Retrieved Images	Proposed	LTP
1	5	5
2	12	11
3	16	15
4	20	19
5	22	21
6	23	22
7	25	23
8	28	24
9	30	24
10	31	25

5. CONCLUSION

In this Work, a new image indexing and retrieval algorithm is proposed using local ternary co-occurrence patterns (LTCoP). The LTCoP encodes the co-occurrence of similar ternary edges in an image. The performance of the proposed method is also analyzed with different thresholds for ternary value calculation. The performance improvement of the proposed method has been compared with the LTP and LTCoP. The result which shows a significant improvement in terms of precision, recall, ARR and ARP as compared to LTP and LTCoP on respective databases. As a result of effectiveness of the proposed method, it can be also suitable for other pattern recognition applications such as face recognition, fingerprint recognition, etc.

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