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Retrieval Of Images Based On Texture And Color Features

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Abstract:
Content-based image retrieval (CBIR) is a new but widely espoused method for finding images from enormous image databases. The need of content based image retrieval technique is in different domains such as medical imaging, crime prevention, weather forecasting, surveillance, historical research and remote sensing. This paper presents the content based image retrieval, using texture and color features. The different features are extracted and the effectiveness of content based image retrieval can be increased. The proposed system has confirmed a faster retrieval method on a COREL image data base and CASIA image database containing 1000 color images and medical images respectively. The performance of this proposed method is evaluated using color image and medical image database and measured using average precision, average recall. The experimental result shows this proposed method has accomplished the highest retrieval rate.

Key words: *Content based image retrieval (CBIR), Gabor filter, Texture, Color.*

1.Introduction

1.1.Image Retrieval

Image retrieval is the technique and process of searching, browsing, recovering, and interpreting information from large amount of stored. There are two research areas study the image retrieval from different angles, one is visual based and other text based. It has been widely recognized that the family of image retrieval techniques should become an integration of both low-level visual features, addressing the more detailed perceptual aspects, and high-level semantic features underlying the more general conceptual aspects of visual data. Image contents are much more difficult compared with text, and the amount of visual data is already enormous and still expanding very rapidly. Low-level visual features such as color, texture, shape and spatial relationships are directly related to perceptual aspects of image content. Since it is usually easy to extract and represent these features and fairly appropriate to design similarity measures by using the statistical properties of these features. Conventional information retrieval is based solely on text, and these approaches to textual information retrieval have been transplanted into image retrieval in a variety of ways, including the representation of an image as a vector of feature values. High-level conceptual information is normally represented by using text descriptors. Traditional indexing for image retrieval is text-based. It is difficult for text to capture the perceptual saliency of visual features. It is rather difficult
to characterize certain entities, attributes, roles or events by means of text only. Although it is an obvious fact that image contents are much more complicated than textual data stored in traditional databases, there is an even greater demand for retrieval and management tools for visual data, since visual information is a more capable medium of conveying ideas and is more closely related to human perception of the real world. Neither of these two types of features is sufficient to retrieve or manage visual data in an effective or efficient way. Although efforts have been devoted to combine these two aspects of visual data, the gap between them is still a huge barrier in front of researchers. How to bridge this gap between visual features and semantic features has been a major

challenge in this research field. To overcome the difficulties an alternative method called Content Based Image Retrieval is used.

1.2.Content Based Image Retrieval

Content-based retrieval uses the contents of images to represent and access the images. A classic content-based retrieval system is alienated into online image retrieval and off-line feature extraction. In on-line image retrieval, a query example of the user can submit to the retrieval system in look for of desired images. The system represents this example with a feature vector. The similarities between the feature vectors of the query example and feature database are then computed and graded. Indexing technique can be used to accomplish the retrieval which provides an efficient way of searching the image database. In off-line image retrieval, each image in the database visual attributes (color, shape, texture, and spatial information) are extracted automatically based on its pixel values and stores them in a different database within the system called a feature database. The feature data also known as image signature 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. The need for human intervention during image indexing and retrieval is to be reduced is the main goal of CBIR.

2.Related Works

Novel approaches referred as Local tetra pattern for content based image retrieval encoded the images based on the direction of pixels are calculated by horizontal and vertical derivatives [1]. The magnitude of binary pattern is collected using magnitudes of derivatives. The effectiveness of the proposed system has been also analyzed by combining it with the GT. The performance improvement of the proposed method has been compared with the LBP, LTP and LDP on grayscale images and gas been detailed below. The average precision has significantly improved from 70.34%, 72.9%, 73.4% to 75.9% as compared with the LBP, LTP and LDP respectively on database DB1. The average recall has improved from 44.9%, 45.8%, 46.9% to 48.7% as compared with the LBP, LTP and LDP respectively. The ARR has improved from 79.7%, 82.5%, 79.91% to 85.3% as compared with the LBP, LTP and LDP respectively. This proposed method has extracted more detailed information based on $(n-1)^{th}$ order derivatives calculation in 0^o & 90^o degrees. It has achieved high average precision and average recall. But it has taken more computational time for retrieving the images.

A novel approach to compute rotation-invariant features from histograms of local non-invariant patterns and this proposed approach to both static and dynamic local binary pattern (LBP) descriptors [2]. For static –texture description, we present LBP histogram Fourier (LBP-HF) features, and for dynamic-texture recognition we present two rotation-invariant descriptors computed from the LBPs from three orthogonal planes (LBP-TOP) features in the spatiotemporal domain. This approach also can be generalized; sign and magnitude components together can improve the description ability, reduces the computational complexity and improve the classification accuracy.

Content-based image retrieval using fused features [3] have presented a method to extract color and texture features using content-based image retrieval. Color and texture features based on a co-occurrence matrix are extracted to form feature vectors. Then the characteristics of the global, local color histograms and texture features are compared and analyzed. CBIR system is designed using color and texture combined features by constructing weights of feature vectors. In addition the performance measure of the system was also discussed. The CBIR process consists of calculating a feature vector that characterizes some image properties, and stored in the image feature database. The user provides a query image, and the CBIR system computes the feature vector for it, and then compares it with the particular image feature database images. The relevance comparison is done by using some distance measurement technique, and the minimum or permissible distances are the metrics for the matched or similar images. The features vector should be able to fully characterize image structural and spatial properties, which retrieve the similar images from the image database.

A Survey On: Content Based Image Retrieval Systems [4] proposed a texture and color histogram based image retrieval. It also introduced the feature like neuro fuzzy technique, color histogram, texture and edge density for accurate and effective Content Based Image Retrieval System. Fuzzy logic has been used extensively in various areas to improve the performance of the system and to achieve better results in different applications.

A smart content-based image retrieval system based on color and texture feature [5] proposed a color-texture and color-histogram based image retrieval system (CTCHIR). They proposed (1) three image features, based on color, texture and color distribution, as color co-occurrence matrix (CCM), difference between pixels of scan pattern (DBPSP) and color histogram for K-mean (CHKM) respectively and (2) a method for image retrieval by integrating CCM, DBPSP and CHKM to enhance image detection rate and simplify computation of image retrieval.

A completed modeling of local binary pattern operator is proposed and an associated completed LBP scheme is developed for texture classification and analyzed LBP from a viewpoint of LDSMT [6]. Three operators CLBP_C, CLBP_S and CLBP_M were defined to extract the image local gray level, the sign and magnitude features of local difference, respectively. This method has improved the texture classification accuracy. The computational time for extracting the feature was high in this method.

Face recognition with high order local derivative pattern is proposed to encode the $(n-1)^{th}$ order local derivative direction variations, which capture more detailed information than the first order local pattern used in local binary pattern(LBP)[7]. Both gray level images and Gabor feature images are used to evaluate the comparative performances of LDP and LBP. Higher order LDP consistently performs much better than LP for both face identification and face verification under various conditions. This method has achieved the better performance and increase the recognition rate. The complexity has increased when partial least square method was not used.

The need for efficient image retrieval is increased tremendously in many application areas such as medical imaging, military, digital library and computer aided design [5]. Image Retrieval Based On Color and Texture Features of the Image Sub-blocks [8] has proposed local color and texture features for efficient image retrieval. An image is partitioned into sub-blocks of equal size as a first step. Color of each sub-block is extracted by quantifying the HSV color space into non-equal intervals and the color feature is represented by cumulative histogram. Texture of each sub-block is obtained by using gray level co occurrence matrix. The average precision for different texture and color feature compared with other image retrieval system shows better performance of the proposed system.

Analysis and Comparison of Texture Features for Content Based Image Retrieval [9], the First-order statistics, second-order statistics, Gabor transform and 2D Wavelet transforms were considered for retrieval. The retrieval efficiency of the texture features was investigated by means of relevance. According to the results obtained it is difficult to claim that any individual feature is superior to others. The performance depends on the spatial distribution of images. The test results indicated that Gray Level Co occurrence Matrix performs well compared to other features when images are homogeneous. It is also noted that the structural texture features are more effective than the statistical texture features. In case of combination features, combinations recorded better retrieval rate compared to the performances of those individual texture features.

Content-based image retrieval approach for biometric security using color, texture and shape features controlled by fuzzy heuristics [10] proposed and described image retrieval approach for biometric security purposes, which is based on color, texture and shape features, controlled by fuzzy heuristics. The proposed approach is based on the three well known algorithms: color histogram, texture and moment invariants. The evaluation is carried out using the standard Precision and Recall measures, and the results are compared with the existing approaches. The presented results show that the proposed approach produce better results as compared to

the existing methods.

3.Proposed Method

The proposed system consists of image acquisition stage, image preprocessing stage, feature extraction stage and image classification stage. Texture and color features are calculated and stored in a database and the features are combined as a Feature Vector. Finally, the system retrieves the similar image to the user on the screen.

The proposed CBIR system flow chart is shown in Figure 1.

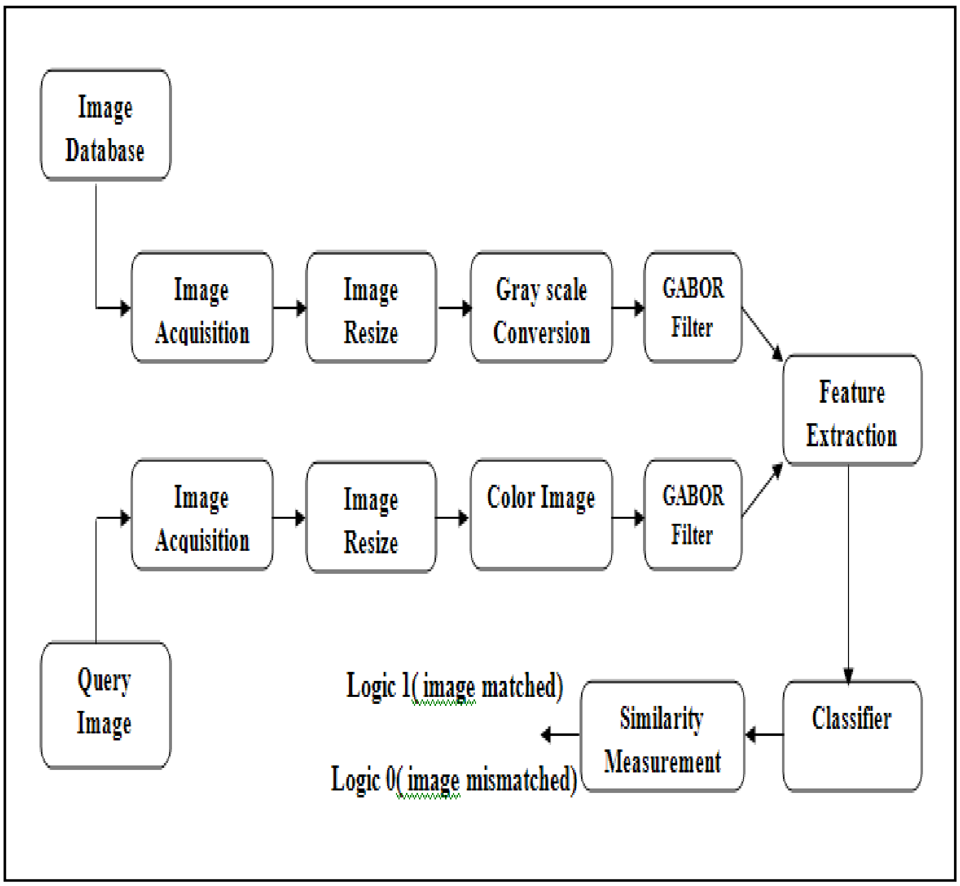

Figure 1: Block diagram of proposed content based image retrieval system

3.1.Gabor Filters

Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific direction and a specific frequency. Expanding a signal using this basis provides a localized frequency description, therefore capturing local features/energy of the signal. A

Gabor filter is a linear filter whose impulse response can be defined by a harmonic function multiplied by a Gaussian function. The Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the Gaussian function and the Fourier transform of the harmonic function due to convolution property. A sinusoidal plane wave has been modulating a 2D Gabor filter which is a Gaussian kernel function in the spatial domain. Gabor filters have the ability to perform multi-resolution decomposition due to its localization both in spatial and spatial frequency domain. Filters with smaller bandwidths in the spatial-frequency domain are more desirable because they allow us to make finer distinctions among different textures. A two dimensional Gabor function consists of a sinusoidal plane wave of some frequency and orientation, modulated by a two-dimensional Gaussian. The Gabor filter in the spatial domain is given by

$$g_{\lambda\theta\psi\sigma\gamma}(x,y) = \exp\left(\frac{-x'^2 + y'^2 \Upsilon^2}{2\sigma^2}\right) \cos\left(2\pi\left(\frac{x}{\lambda} + \psi\right)\right) \qquad (1)$$

where $x' = x\cos\theta + y\sin\theta$

$y' = y\cos\theta - x\sin\theta$

In this equation λ represents the wavelength of the cosine factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function in degrees, ψ is the phase offset in degrees, and Υ is the spatial aspect ratio and specifies the elliptically of the support of the Gabor function, and σ is the standard deviation of the Gaussian determines the (linear) size of the receptive field. When an image is processed by a Gabor filter, the output is the convolution of the image I(x, y) with the Gabor function g(x,y).

$$r(x,y) = I(x,y) * g(x,y) \qquad (2)$$

3.2.Texture Feature Extraction

Texture can be described as the repeated patterns of pixels over a spatial domain. Texture properties are the visual patterns in an image that have properties of homogeneity that do not result from the presence of only a single color or intensity. It comprises important information about the structural arrangement of the surface i.e., clouds, leaves, bricks, fabric, etc. The different texture properties as perceived by the human eye are regularity, directionality, smoothness and coarseness. It also depicts the relationship of the surface to the surrounding environment. It is a feature that demonstrates the distinctive physical composition of a surface.

Texture measures are classified into first order statistics and second order statistics. First-order texture measures are computed from the original image values. They do not consider the relationships with neighborhood pixel. The first order statistics are mean, standard deviation, energy, entropy, skewness and kurtosis. Therefore, the histogram contains the first-order statistical information about the image (or sub image).

The gray-level co-occurrence matrix (GLCM) or gray-level spatial dependence matrix based calculations fall under the category of second-order statistics. Haralick *et. al.* [13] suggested a set of textual features which contain information about image textural characteristics and which can be extracted from the co-occurrence matrix, such as homogeneity, contrast and entropy.

A gray level co-occurrence matrix (GLCM) restrains information about the positions of pixels having similar gray level values. It is a two-dimensional array, P, in which both the rows and the columns represent a set of possible image values. GLCM is composed of the probability value, it is defined by which expresses $P(i,j\,|d,\theta)$ the probability of the couple pixels at θ direction and d interval. When θ and d is determined, is showed by $P(i, j)$. Distinctly GLCM is a symmetry matrix and its level is determined by the image gray-level. Elements in the matrix are computed by the equation given below:

$$P(i,j|d,\theta) - \frac{P(i,j \mid d,\theta)}{\sum\sum P(i,j|d,\theta)} \quad (3)$$

GLCM expresses the texture feature dealing the correlation of the gray-level value of pixels at different positions. In this paper, five texture features are extracted. They include energy, contrast, entropy, correlation and homogeneity.

$$\text{Energy (E)} = \sum\sum P(x,y)^2 \quad (4)$$

It is a texture measure of gray-scale image represents homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

$$\text{Contrast (I)} = \sum\sum (x-y)^2 P(x,y)^2 \quad (5)$$

Contrast measures how the values of the matrix are distributed and number of images of local changes reflecting the image clarity and texture of shadow depth. Large Contrast represents deeper texture. Otherwise Contrast returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

$$\text{Entropy (S)} = -\sum\sum P(x,y) \log P(x,y) \quad (6)$$

Entropy is a measure of information content. It measures randomness in the image texture. It is minimum when the co-occurrence matrix for all values is equal. On the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random.

$$\text{Correlation (C)} = \sum\sum \frac{(X-Mr)(y-mc)Pxy}{\sigma x \sigma c} \quad (7)$$

Correlation measures how a pixel is correlated to its neighbor over the entire image and its range lies between 1 and -1 which is defined as follows,

$$\text{Homogeneity(H)}= \sum\sum \frac{P(x,y)}{1+|x-y|} \qquad (8)$$

Homogeneity returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

3.3.Color Feature Extraction

The method of representing color information of images in CBIR systems is through color histograms. A color histogram is a type of bar graph, where each bar represents a particular color of the color space being used. In other words it gives the count of pixels in an image representing a particular color. There are two types of color histograms, Global Color Histograms (GCHs) and Local Color Histograms (LCHs). A GCH represents one whole image with a single color histogram. An LCH splits an image into fixed blocks and the color histogram of each of those blocks are obtained. LCHs contain much more information about an image but are computationally expensive when comparing images. “The GCH is the traditional method for color based image retrieval. However, it does not include information concerning the color distribution of the regions” of an image. Thus when comparing GCHs one may get inconsistent result in terms of similarity of images.

3.4.Color Histogram

Color represents one of the most widely used visual features in CBIR systems. Each pixel of a image is associated to a specific histogram bin only on the basis of its own color, and color similarity across different bins or color dissimilarity in the same bins are not taken into account. Here three components like red, green, blue in RGB space are used. For the color histogram, the distribution of the number of pixels for each quantized bin can be defined for each component. Quantization in terms of color histograms refers to the process of reducing the number of bins by taking colors that are very similar to each other and putting them in the same bin. The comparison between images (query image and image in database) is accomplished through the use of some distance metric which determines the distance or similarity between the two histograms.

4.Results And Discussion

Performance Analysis

$$\text{Average Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}$$

$$\text{Average Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in the data base}}$$

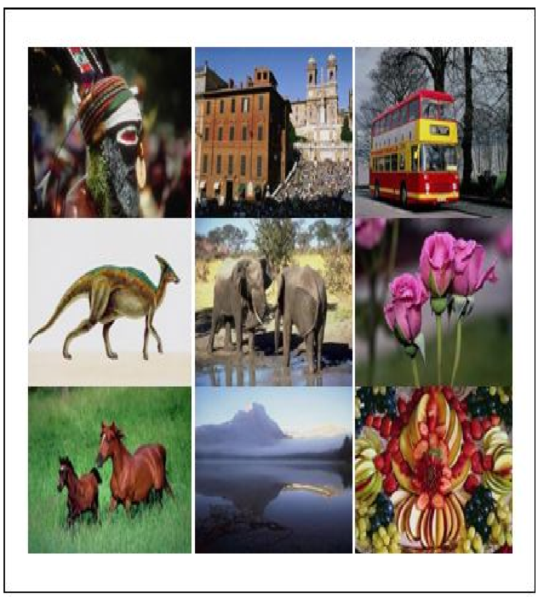

Figure 2: Sample images from COREL data base

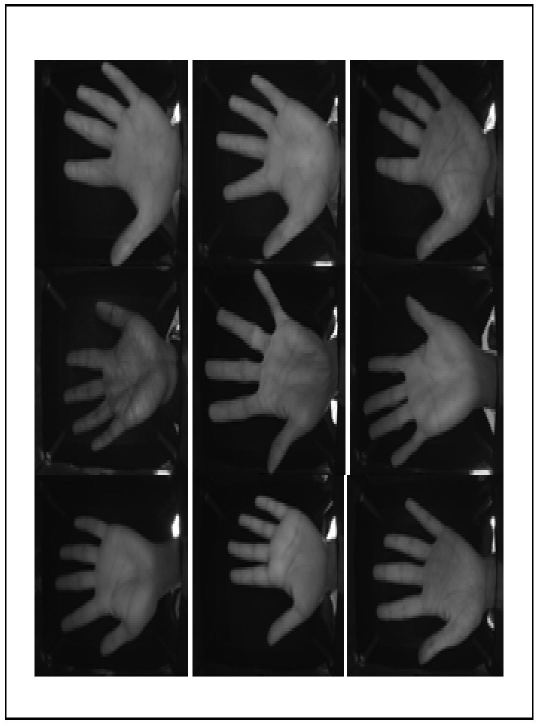

Figure 3: Sample images from CASIA data base

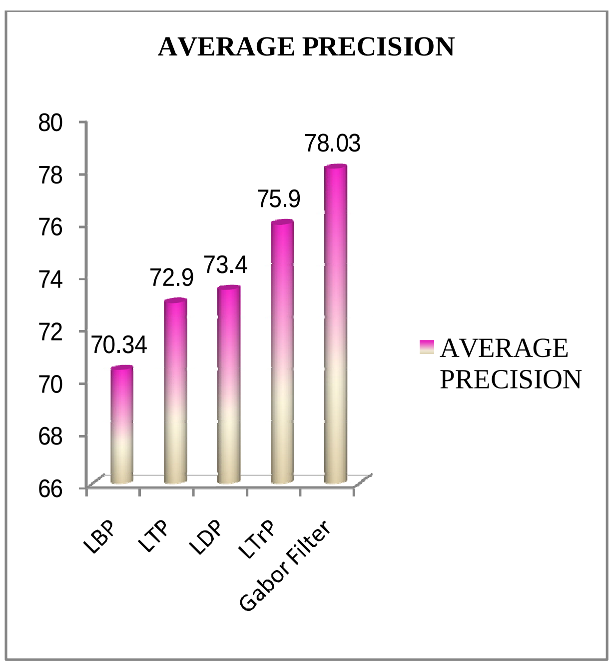

Figure 4(a): Performance comparisons between LBP, LTP, LDP, LTrP and Gabor filter-Average Precision

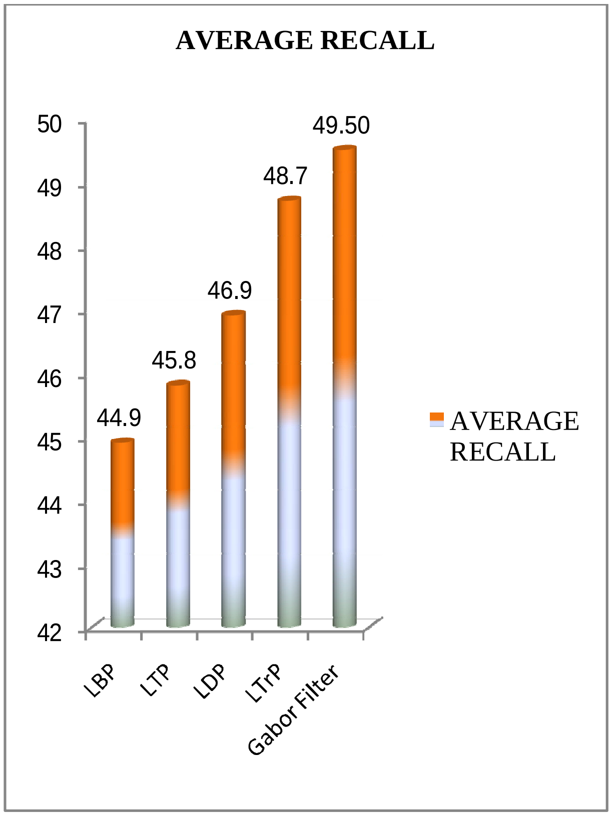

Figure 4 (b): Performance comparisons between LBP, LTP, LDP, LTrP and Gabor filter- Average Recall

From the Figure (a) and (b) the average precision and average recall for the proposed method has increased compare with the existing systems.

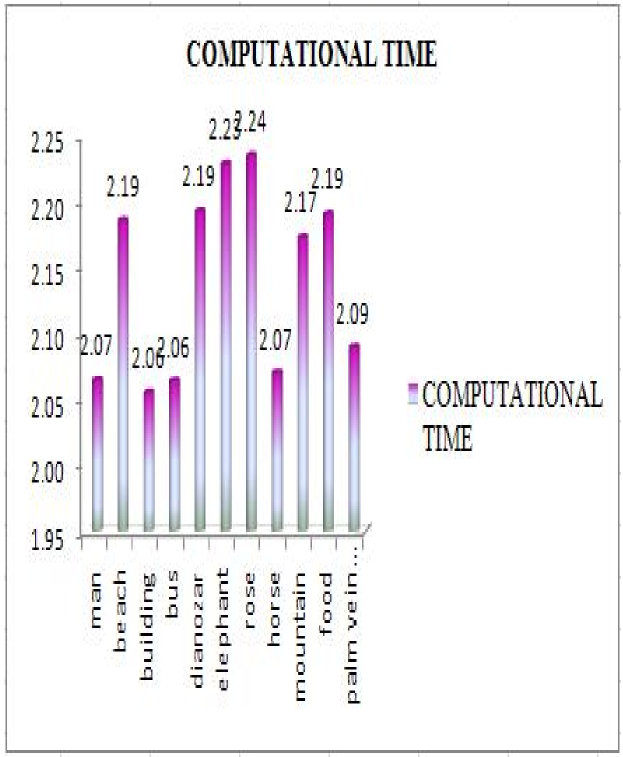

Figure 5: Computational time for different images in data base

From the Figure 5 the computational time for different images has obtained and it will show that the natural images take more computation time compare with the palm vein images during retrieving process but compare with existing schemes it has reduced. The proposed system has achieved the 95.6 % of average retrieval rate compare with existing methods.

5.Conclusion

The proposed system presents the texture and color feature extraction. This method is able to obtain the good precision and recall compare with the existing methods. The experimental results shows the high retrieval rate and reduced computational time compare with the LBP, LDP, LTP, LTrP for COREL database and CASIA palm vein data base images. The performance improvement of the proposed method has been compared with the LBP, the LTP, the LDP and the LTrP on grayscale images and color images has been detailed below. The average precision has significantly improved from 70.34%, 72.9%, 73.4% and 75.9% to 78.03% as compared with the LBP, the LTP, the

LDP and the LTrP respectively, on database DB. The average recall has improved from 44.9%, 45.8%, 46.9% and 48.7% to 49.50%, as compared with the LBP, the LTP, and the LDP, the LTrP, respectively, on database DB. The average retrieval rate has improved from 82.23%, 87.52%, 87.27% and 90.02% to 95.6% as compared with the LBP, LTP, LDP and the LTrP respectively on database DB. Due to effectiveness of the proposed method this will be suitable for pattern recognition application and also useful to retrieve the best information from the video images.

6.Reference

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