Content Based Image Retrieval System: A Comparative Analysis of Texture Feature and 3D Colour Histogram

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ABSTRACT

The visual content of an image can be used to search for similar images based on user interest from a large database, in the art known as Content Based Image Retrieval (CBIR). In CBIR systems, the user provides a query image to the system, the system obtains the feature vector, which is compared with certain image features of the images in the database. The adequacy of the feature vectors extracted for the retrieval of appropriate and exact image from the database is an open issue which calls for continual research and attention. This work carried out the retrieval of similar images based on the content of the image by comparing the feature vectors of the queried image and those of the image database using Mahalanobis distance measure. Textural feature vectors of the images were obtained using local binary pattern and 3D colour histogram feature vectors were also extracted. The performances of these two different feature vectors were compared based on the distance metrics to determine their suitability. The similar images in the database are displayed along with their similarity distance value, in which the minimum distance is a metric for the matched images. The CBIR system was implemented using a locally acquired database of over 600 images. Various images were used to query the system, which was able to successfully output similar images. The simulation result obtained revealed that textural feature vectors are more adequate in terms of speed and accuracy in content based image retrieval than 3D colour histogram based on the images used in the experiment.

Keywords: Image retrieval, texture feature, histogram, content based, image descriptors

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1. BACKGROUND

Content Based Image Retrieval (CBIR) is a progressing research area in computer vision and billions of digital images are being produced on the internet as a result of the World Wide Web and Internet of Things (IoT). Due to the Complexity of image data, there is need to establish an appropriate representation and manipulation technique so as to ensure that the information content of the images can be used. (Nagaraja and Prabhakar, 2015). One of the key issues with any kind of image processing is the need to extract useful information from the raw data (such as recognizing the presence of particular shapes or textures) before any kind of reasoning about the image's contents is possible. CBIR leads to great savings in time and pressure especially in the fields that deals with image database or image files whose contents is depicted by simple keywords or texts.

CBIR provides an efficient and effective way to manage large image databases and efficiently run image retrievals to get the best results without exhaustively searching the global database several time (Pinjarkar, Sharma and Mehta 2012). Content based image retrieval is a technique which uses visual contents to search images from large database according to user interest. It has been an active and fast advancing research area over the last few years, fuelled at least in part by the rapid growth of imaging on the World-Wide Web. Users are exploiting the opportunity to access remotely-stored images in all kinds of new and exciting ways (Sandhu and Kochhar, 2012).

This has exacerbated the problem of locating a desired image in a large and varied collection. However, with CBIR, the retrieval of images on the basis of features automatically extracted from the images themselves is made possible. Content-Based Image Retrieval has been used in several applications, such as medicine, fingerprint identification, biodiversity information systems, digital libraries and crime prevention to mention a few. The term "content" in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because searches that rely purely on metadata are dependent on annotation quality and completeness (Sandhu, Kochhar in 2012).

The process of content-based image retrieval consists of computing a feature vector that characterizes the nature of the images. The images are stored in a feature database. The user then provides a query image and the system calculates the feature vector, and then compares it with a certain image features of the image database. Comparisons can be made by using a distance measurement technique, and the minimum distance is a metric for the matched or similar images. Feature vectors should be capable enough to fully characterize the structural and spatial image properties, of the images in the database (Afifi and Ashour, 2012). Content-based retrieval systems utilize measures that are based on low-level attributes of the image itself, including colour histograms, colour composition, and mixture. State-of-the-art research focuses on more powerful measures that can find regions of an image corresponding to known objects that users wish to retrieve (Nagaraja and Prabhakar, 2015). Appropriate feature representation which can give rise to a fast and accurate retrieval of desired users request (query image) is fundamental to this research.

2. RELATED WORK

Muyeba, Khan, Coene in 2009 proposed a system for image mining using fuzzy rule. It relates the property of composite attributes. They partitioned the property value into fuzzy property sets. The limitation of this work was that fuzzy measures and correlation association was not described. Jiang and Tan in 2009 proposed two methods for discovering the underlying associations between text and images. The first method based on transformation measures the information similarity between visual features and textual features. Another method uses a neural network to learn direct mapping between visual and text features by incrementally summarizing associated features into a set of information template. The limitation of this work is that it needs to perform batch learning on a fixed set of training data.

Dubey in 2010 illustrated an image mining method which is dependent on the color Histogram, texture of that image. The query image is considered, then the COLOR Histogram and Texture is created and in accordance with this the resultant image is found. In this approach, the limitation is that computing time for RGB color space not considered. Pinjarkar, Sharma and Mehta 2012 discussed various methodologies used in the research area of Content Based Image Retrieval techniques using Relevance Feedback. To improve the retrieval performance of the CBIR the Relevance Feedback technique can be incorporated in CBIR system to obtain the higher values of the standard evaluation parameters used for evaluation of the CBIR system which may lead to better results of retrieval performance. He also discussed various relevance feedback techniques for Content Based Image Retrieval systems, the various parameters used for experimental evaluation of the systems and the analysis of these techniques on the basis of their results.

Gueguen and Datcu in 2007 addressed the problem of extracting relevant information from Satellite image time series (SITS) based on the information-bottleneck principle. The method depends on suitable model selection, coupled with a rate–distortion analysis for determining the optimal number of clusters. They presented how to use this method with the Gauss–Markov random fields and the auto binomial random fields model families in order to characterize the spatio-temporal structures contained in SITS. The limitation in this research approach was that spectral or geometrical information was not taken into account. Rajendran and Madheswaran in2009 discussed an image mining technique. It combines low level features extracted from images and high level knowledge from specialist. The problem with this approach is that it does not addressed feature redundancy, image noise and time complexity.

Sandhu, Kochhar in 2012 presents a technique for content based image retrieval using texture, color and shape for image analysis. In this paper they worked with the three features i.e. texture, color and shape and its different combinations. The gray level co-occurrence matrix (GLCM) is used for texture feature extraction, histogram for Color feature extraction and for shape different factors are found like area, Euler No., eccentricity and Filled Area. Shambharkar and Tirpude in 2011 proposed a technique for image retrieval using fuzzy-c mean clustering. In this they said an optimization model or objective function must be devised to search for the optimal partition according to the chosen objective function. The way that most researchers have solved the optimization problem has been through an iterative locally optimal technique, called the FCM algorithm and hence they suggested a fuzzy-c mean algorithm.

Singha and Hemachandran in 2012 presents a technique for content based image retrieval using color and texture. In this they proposed two algorithms for image retrieval based on the color histogram and Wavelet-based Color Histogram. They presented a novel approach for Content Based Image Retrieval by combining the color and texture features called Wavelet-Based Color Histogram Image Retrieval (WBCHIR). Similarity between the images is ascertained by means of a distance function. The limitation with this work is that the computational steps are effectively reduced with the use of Wavelet transformation.

Chang, Lin, Ho, Fann, and Wang in 2012 proposed a novel content based image retrieval system using K-means/KNN with feature extraction. This paper first combines segmentation and feature extraction module, grid module, K-means clustering and neighbourhood module to build the CBIR system. The problem with this technique is that the system architecture and modules proposed in this paper are not optimized properly. Patil and Kokare in 2011 provides an overview of the technical achievements in the research area of Relevance Feedback (RF) in Content-Based Image Retrieval (CBIR). It also covers the current state of art of the research in relevance feedback in CBIR, various relevance feedback techniques and issues in relevance feedback were reported which serves as a guide for interested researchers in the field.

3. MATERIALS AND METHOD

The CBIR system was implemented using a locally acquired database of over 600 images, from different sources and they all varies in resolution and have different file formats ranging from .jpg, .png, and .bmp. The images were grouped into 6 folds: 100, 200, 300, 400, 500, 600 images. This was done arbitrarily to test the effect of database size on the speed of image retrieval.

The feature vectors were extracted using the following procedure:

i. Gather colour images of different sizes and format from various sources to populate the database
ii. Create the 3D histogram template using the intensities of the 3 colour channels in an image and store the feature vectors.
iii. Obtain the local binary pattern of the images to create the textural template
iv. Using Mahalanobis distance as a similarity measure, calculate the histogram distance function as well as the textural distance function.
v. Test the system by querying it with an image and measuring the precision of similar images returned.

The extraction of the feature vectors using the two methods is detailed in the subsections below.

3.1. Extraction of Textural feature vectors

The identification of specific textures in an image is achieved primarily by modeling texture as a two-dimensional gray level variation. Textures are characterized by differences in brightness with high frequencies in the image spectrum. The Local Binary Pattern algorithm is employed which divides the image into equal sub regions, threshold using the centre pixel and obtains the pattern of each region. The pattern obtained is concatenated to form a larger pattern which represents the texture of the image. The features obtained are high-order statistical features which represents the statistics of gray level differential.

This was obtained using equations 3.1, 3.2 and 3.3 respectively.

$$LBP(x_c, y_c - \sum_{n=0}^{7} s(i_n, i_c) 2^n) \qquad (3.1)$$

where
i_c corresponds to the grey value of the center pixel (x_c, y_c)
i_n to the grey values of the 8 surrounding pixels, and
function s is defined as:

$$s(x) = \begin{cases} 1 \; if \; x \geq 0 \\ 0 \; if \; x < 0 \end{cases} \qquad (3.2)$$

The choice of radius R and number of pixel in the neighbourhood P was done using circular neighbourhood and linearly interpolating the pixel values as shown in equation 3.3.

$$LBP_{P,R}(x,y) = \sum_{P=0}^{P-1} s(g_P - g_C) 2^P \qquad (3.3)$$

where g_p is the neighbourhood and g_c is the centre pixel.

The LBP operator was used to transform an image into an array of integer labels describing small scale appearance of the image which represents the feature vectors.

3.2. Extraction of 3D colour histogram feature vectors
The 3D colour histogram can be built for any kind of colour space. Like other kinds of histograms, the colour histogram is a statistic that can be viewed as an approximation of an underlying continuous distribution of colour values. The color histogram is formerly defined by equation 3.4.

$$h_{A,B,C}(a,b,c) = N.Prob(A = a, B = b, C = c)\ldots \quad (3.4)$$

where *A* , *B* and *C* represent the three colour channels (R,G,B or H,S,V) and *N* is the number of pixels in the image.

The colour histogram was formed by discretizing the colours within an image and counting the number of pixels of each colour.

Since the typical computer represents colour images with up to 224 colours, this process generally requires substantial quantization of the colour space. The RGB colour space has limited uniformity in terms of colour distribution hence, the HSV colour which represents with equal emphasis the three colour variants that characterize colour: Hue, Saturation and Value is considered. Therefore, the RGB values are converted to HSV values. The 3D (HSV) histogram of the image is computed and the number of bins in each direction (i.e., HSV space) is duplicated by means of interpolation to obtain the resultant feature vectors. The feature vectors obtained by the two algorithms were separately indexed into .mat file in MATLAB. This represents the feature vectors of the trained images in the image database. The Mahalanobis distance takes into account the covariance among the variables in calculating distances. With this measure, the problems of scale and correlation inherent in the Euclidean distance are no longer an issue, the more reason it was adopted in this research. The Mahalanobis distance from x to y is calculated using:

$$D_i^{Mahalanobis} = \sqrt{(x - yi)^T \Sigma_i^{-1} (x - yi)} \qquad (3.5)$$

The Mahalanobis distance is measured in terms of standard deviations from the mean of the training samples, hence the reported matching values give a statistical measure of how well the spectrum of the unknown sample matches (or does not match) the original training spectra as earlier stated.

4. RESULTS AND DISCUSSION

The CBIR system was tested by querying with the images that were not part of the train database to test for the validity of the system. When a tested image has been prompted and queried, the query image loops into the whole database generate its 3D HSV histogram, and on the other hand, the LBP descriptors. The Mahalanobis distance between a sample query image in Figure 4.1 and the images in the database is being calculated. Similar images based on the closest distance are outputted as shown in Figure 4.2.

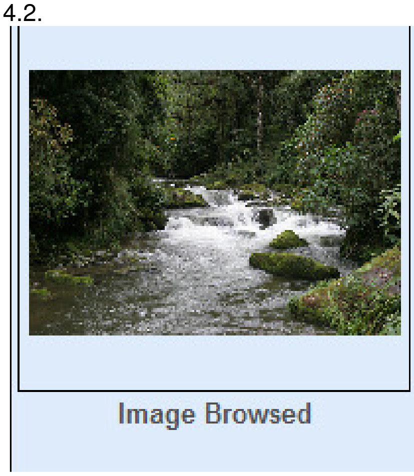

Figure 4.1. A query image

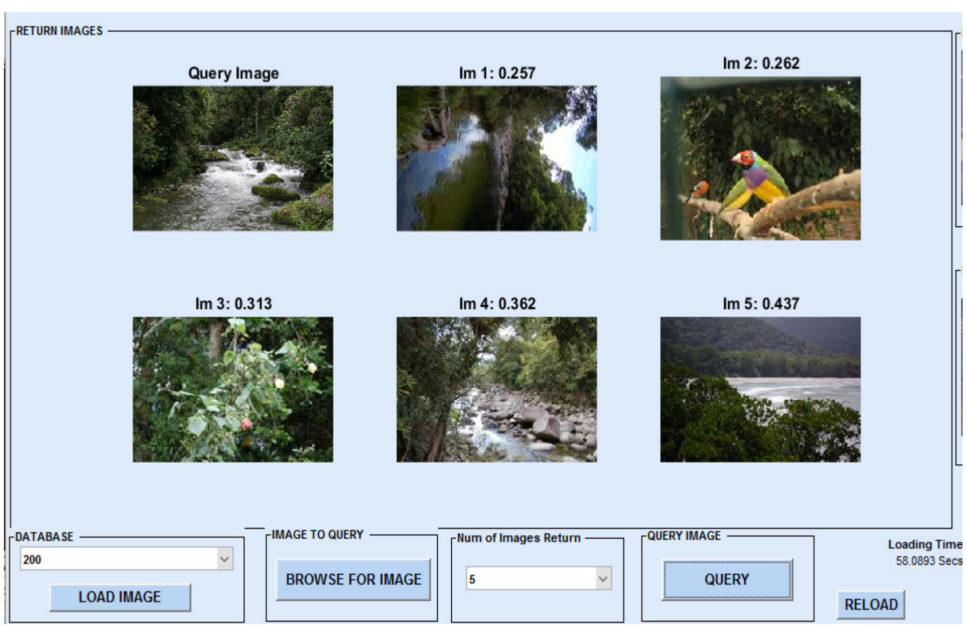

Figure 4.2. Similar matches from the database.

The image with the least distance is the most similar to the queried image, therefore, the smaller the distance, the closer the match. The time taken to retrieve the similar set of images is a major computational issue to be considered in building a real time image retrieval system. Also, the exactness of the image retrieved as the similar match for the queried image is very important. In this research the result obtained for retrieval time and correctness of displayed similar images is tabulated in Table 4.1 for the textural features and the 3D histogram, using the same distance metrics. It can be observed from the table that the retrieval time increases as the database size increases. This could be as a result of increase in the number of images to be compared with the query image so as to determine the similar match.

It can also be observed from the result that texture feature vector outperforms 3D histogram feature both in terms of exactness of retrieved image as well as retrieval time.

Table 4.1:Comparative analysis of 3D Colour Histogram and Texture feature

	3D COLOUR HISTOGRAM						TEXTURE FEATURE					
Number of Images in a set	100	200	300	400	500	600	100	200	300	400	500	600
Retrieval time of similar images	0.38	0.49	0.67	0.90	1.23	1.56	0.15	0.31	0.52	0.74	0.97	1.05
Exactness	86	174	263	359	462	540	91	190	293	389	487	589

5. CONCLUSION AND FUTURE DIRECTION

In this research, an overview of the field of image retrieval was carried out and the effect of two different types of feature representation was examined for Content-Based Image Retrieval Systems. Experimenting using the Mahalanobis Distance measure for calculating the similarity between the query image and the images in the database shows that the textural feature vectors outperforms the 3D colour histogram features. This implies that the textural feature vectors were able to optimize the response time of the retrieval system. Future work includes experimentation of the technique on medical image data sets such as liver dataset. Also, other feature vector representation techniques will be researched into.

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