



A COMPARATIVE ANALYSIS OF TEXTURE FEATURE AND 3D COLOUR HISTOGRAM FOR CONTENT BASED IMAGE RETRIEVAL

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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 presents 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 involved 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 different images. Various images were used to query the CBIR 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

INTRODUCTION

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). The complexity of image data has necessitated the 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 demands especially in the fields that deal with image database or image files whose contents are depicted by

simple features, 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 times (Pinjarkar, et, al. 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 and Kochhar, 2012). The process of content-based image retrieval consists of computing a feature vector that characterizes the nature of the images (Drimbarean and Whelan, 2011). 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). Uninformative features produce bad predictions; therefore, appropriate feature representation which can give rise to a fast and accurate retrieval of desired user's request (query image) is fundamental to this research. Muyeba, *et. al* (2009) proposed a system for image mining using fuzzy rule. It relates the property of composite attributes. The property value was partitioned into fuzzy property sets. The limitation of this work was

that fuzzy measures and correlation association was not described. Jiang and Tan (2009) proposed two methods for discovering the underlying associations between text and images. The first method based on transformation measured the information similarity between visual features and textual features. Another method used 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 was that it needed to perform batch learning on a fixed set of training data. Dubey (2010) illustrated an image mining method which is dependent on the color histogram, texture of that image. The query image was considered, then the COLOR Histogram and Texture was created and in accordance with this the resultant image was found. The limitation was that computing time for RGB color space was not considered. Pinjarkar, *et al* (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. Gueguen and Datcu (2007) addressed the problem of extracting relevant information from Satellite image time series (SITS) based on the information-bottleneck principle. The method depended on suitable model selection, coupled with a rate-distortion analysis for determining the optimal number of clusters. The work presented the use of 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 (2009)

discussed an image mining technique. It combined low level features extracted from images and high level knowledge from specialist. The problem with this approach was that it did not address feature redundancy, image noise and time complexity. Sandhu and Kochhar (2012) presented a technique for content based image retrieval using texture, color and shape for image analysis. These three features were combined differently to explore the effect on image retrieval. The gray level co-occurrence matrix (GLCM) was used for texture feature extraction, histogram for color feature extraction and eccentricity and filled area for shape feature extraction. The texture features was found to outperform the shape and colour feature. Singha and Hemachandran (2012) presented a technique for content based image retrieval using color and texture. The work proposed two algorithms for image retrieval based on the color histogram and Wavelet-based Color Histogram. The outcome was 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 was ascertained by means of a distance function. The limitation with this work was that the computational steps involved with the hybrid model was time consuming.

Chang, *et al*, (2012) proposed a novel content based image retrieval system using K-means/KNN with feature extraction. The work combined segmentation and feature extraction module, grid module, K-means clustering and neighbourhood module to build the CBIR system. The problem with this technique was that the optimisation process of the system architecture and modules resulted in a model with high computational complexity. Patil and Kokare (2011) provided an overview of the technical achievements in the research area of Relevance Feedback (RF) in Content-Based Image Retrieval (CBIR). The work also covered 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 served as a guide for interested researchers in the field. A typical architecture of a CBIR system is shown in Fig.1.

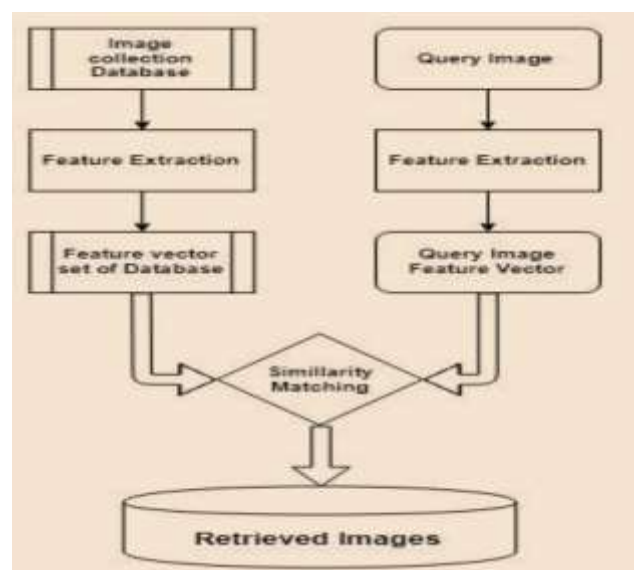


Fig. 1: Architecture of a CBIR system

Table 1: CBIR (Content Based Image Retrieval) current research works

<i>Author(s)</i>	<i>Method</i>	<i>Database</i>	<i>Observation</i>
Kaur and Sohi, (2016)	Combines HSV and Gabor filters	N/A	Hybrid features are found to be computationally intensive
Yinghui et. al (2018)	GLCM, a second order texture feature extractor	breast cancer images	Employs sequential matching, which was time consuming
Dahake and Thakari (2018)	Uses Gabor filters	N/A	Filter features are slow and computationally intensive

However, there are recent related research in the area of CBIR as highlighted in Table 1, and this research sought to identify a suitable feature representation for the process of retrieval of images based on content.

MATERIALS AND METHOD

The CBIR system was implemented by populating a locally acquired database of over 600 images, from different sources and they all varied in resolution and had different file formats ranging from .jpg, .png, and .bmp. The images were grouped into 6 folders, containing 100, 200, 300, 400, 500 and 600 images per folder. This was done arbitrarily to test the effect of database size on the speed of image retrieval. At first, 3D histogram feature template was extracted using the intensities of the 3 colour channels (RGB) in an image and the features were stored in vectors. Secondly, the local binary pattern of the images were extracted to create the textural feature template. The Mahalanobis distance metrics was used as a similarity measure to calculate the histogram distance function as well as the textural distance function. The system was tested by querying with an image and measuring the precision of similar images returned.

The extraction of the feature vectors were achieved using the two methods viz Extraction

of Textural feature vectors and Extraction of 3D colour histogram feature vectors.

Extraction of Textural feature vectors

The identification of specific textures in an image was achieved primarily by modeling texture as a two-dimensional gray level variation. Textures were characterized by differences in brightness with high frequencies in the image spectrum. The Local Binary Pattern algorithm was employed which divides the image into equal sub regions, threshold using the centre pixel to obtain the pattern of each region. The pattern obtained was concatenated to form a larger pattern which represents the texture of the image. The features obtained were high-order statistical features which represents the statistics of gray level differential. These are the texture feature vectors, obtained using equations 3.1, 3.2 and 3.3 respectively.

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

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:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \quad (3.2)$$

The choice of radius R and number of pixel in the neighbourhood P was done using circular

neighbourhood and linearly interpolating the

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p \quad (3.3)$$

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. A sample texture feature obtained from LBP computation is shown in Figure 2.

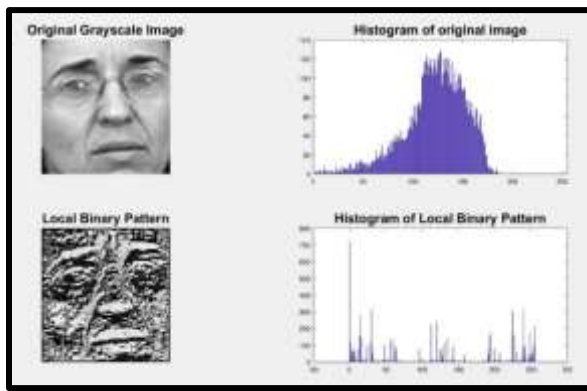


Fig. 2: Sample original image and texture feature of a face image

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.

$$h_{A,B,C}(a,b,c) = N \cdot \text{Prob}(A = a, B = b, C = c) \dots (3.4)$$

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. The *hist* function in MATLAB was used to obtain the 3D histogram. Since the typical computer

pixel values as shown in equation 3.3. 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 are considered. Therefore, the RGB values were converted to HSV values. The 3D (HSV) histogram of the image was computed and the number of bins in each direction (i.e., HSV space) was duplicated by means of interpolation to obtain the resultant feature vectors. A sample 3D colour histogram of an image is shown in Fig 3.

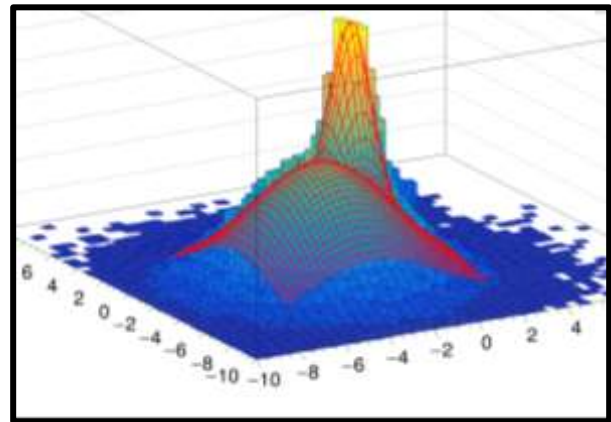


Fig 3: Sample 3D colour histogram of an image

The feature vectors obtained by the two algorithms were separately indexed into .mat file in MATLAB. This represented the feature vectors of the trained images in the image database. The Mahalanobis distance took 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:

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

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.

RESULTS AND DISCUSSION

The CBIR system was tested by querying the images that were not part of the train database in order to test for the validity of the system. When a test image has been prompted for query, the queried 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 and the images in the database is being calculated. Similar images based on the closest distance are outputted in that regard. 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 proportion of positive identification that was actually correct (precision) and the proportion of actual positives that were identified correctly (recall) of the image retrieved 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 2 for the textural features and the 3D histogram, using the same distance metrics. It can be observed from the table that the retrieval time increased as the database size increased for both the 3D features and texture features. 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 retrieval time, precision and recall.

Table 2: Comparative analysis of 3D Colour Histogram and Texture feature

<i>Number of images in a test set of data base</i>	<i>Retrieval time of similar images (secs)</i>		<i>Precision (%)</i>		<i>Recall (%)</i>	
	<i>3D Colour Histogram feature</i>	<i>Texture feature</i>	<i>3D Colour Histogram feature</i>	<i>Texture feature</i>	<i>3D Colour Histogram feature</i>	<i>Texture feature</i>
100	0.38	0.19	91	96	93	98
200	0.59	0.28	86	94	89	96
300	0.88	0.40	83	91	82	95
400	1.34	0.62	77	88	74	93
500	1.87	1.19	71	87	68	91
600	2.41	1.88	69	83	62	90

The implication of the simulation result presented in Table 2, as also reported by previous research is that texture feature outperformed colour and shape features. As reported by Yinghui *et. al.* (2018), which uses GLCM texture feature for CBIR, the LBP texture feature representation used in this research are higher order statistical features which reveals more local primitive features in its texture representation. This is evident in the retrieval time of similar images as well as precision and recall values obtained in this research. The performance metrics such as retrieval time, recall and precision are important parameters for evaluating the behaviour of a classification system towards differences in datasets, feature vector representation and classifiers. A vast number of previous research are not explicit on the empirical result of those aforementioned metrics. Reporting this is one of the contributions of this research.

CONCLUSION

In this research, an experimentation 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. It is hereby recommended that Experimentation of the technique be carried out on medical image data sets such as liver and electrocardiogram (ECG) data.

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