Optimized Content based Image Retrieval System based on Multiple Feature Fusion Algorithm

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ABSTRACT
Recent years have envisaged a sudden increase in the use of multimedia content like images and videos. This increase has created the problem of locating desired digital content from a very large multimedia database. This paper presents an optimized Content Based Image Retrieval (CBIR) system that uses multiple feature fusion and matching to retrieve images from a image database. Three features, namely, color, texture and shape are used. A modified color histogram is used to extract color features, the standard DWT method was combined with Rotated Wavelet Filter (RWF) features and dual tree complex wavelet transform (DT-CWT) are combined to select texture features and active contour model is used to select the shape features. K-means and SOM algorithms are used for clustering and dimensional reduction. The similarity measure used combines spatial distance, direction distance and Euclidean distance during matching process. Experimental results prove that the proposed CBIR system is an improved version in terms of precision, recall and speed of image retrieval.

Keywords: Color histogram, Content Based Image Retrieval, Rotated Wavelet Filter, Dual Tree Complex Wavelet Transform, Self Organizing Map

1. INTRODUCTION
The usage of multimedia objects like images, video and audio has envisaged a tremendous growth in the information and communication media. This growth is mainly contributed by the various sophisticated hardware and software of the current information explosion era, which facilitate ease of creation, storage and distribution of multimedia content. Professionals in various domain areas, like satellite and medical, access and use these images to exploit and discover new trends and patterns in geographical changes and common disease patterns. The main difficulty faced by these professionals is the process of locating desired images from a very large image database. Solution to such situations has created Content Based Image Retrieval (CBIR) systems, which are now widely recognized as image search solutions.

In spite of its wide popularity, the field has not yet reached its maturity and is not yet being used on a significant scale. The usage statistics shows a diversified opinion on the usefulness and effectiveness of CBIR systems in handling queries on large and diverse real-life image databases. This shows that the research area is still active and methods to improve existing solutions are in great demand.

A CBIR system is defined as a task which uses an amalgamation of techniques, like statistics, image processing and pattern recognition, with the aim of searching and retrieving images from a large image database that match a given query in an efficient manner. The query can either be an example image or a sketch, text or terms of keywords. Traditionally, an image is represented by its features such as the color, texture and shape of objects. A great amount of work proposed use algorithms that perform similarity matching on any one of the various available features of the image. Only recently, the usage of multiple features for image retrieval is being gaining attention (Ha *et al.*, 2008, Vadivel *et al.*, 2009). It has been discovered that the retrieval performance, in terms of recall and precision, is enhanced when multiple feature vectors are used. The reason for this performance increase is that single features extracted from images characterizes different aspects of an image content, which when combined to form multiple features, provide an adequate and more accurate description of image content (Deselaers *et al.*, 2008). CBIR system using multiple features extracts more than feature from the image and performs retrieval process in two manners. The first type merge the multiple feature vectors to create a global index while the second method create separate index structure for each feature and then merge the results. The result of fusion is then used during retrieval and indexing. This paper considers the first type, that is, feature level fusion.

The feature level fusion for effective image retrieval is considered challenging because of various reasons. They include, (i) incompatibility issues raised because of the multiple modalities of the features (ii) compatibility issues raised because of the unknown relationship between the feature spaces (iii) 'Curse of Dimensionality' issue raised because of the huge feature vector created by concatenating the various feature vectors. In this paper, fusion at the feature level in 3 different contexts is discussed. (i) fusion of Color and Texture features (ii) fusion of Shape and Texture features and (iii) fusion of color, texture and shape features. A novel fusion distance measure that combines Euclidean distance and is used for similarity matching.

This paper is an extension of the authors' previous work (Priya and Vasanthakalyani David, 2010), where an enhanced CBIR system based on Self Organizing Map (SOM) and histogram was proposed. This system integrated the spatial information with enhanced color histograms. In this paper, this work is extended to consider multiple features, enhanced color histogram, texture and shape that are combined with SOM for dimensionality reduction. The initial work is referred to as 'SOM-Colour CBIR System', while the proposed system is referred to as 'Fusion-SOM CBIR System' in this paper. The rest of the paper is organized as below. Section 2 presents a brief review of the studies related to the topic. Section 3 presents the proposed methodology and the results from various experiments are discussed in Section 4. The work is concluded with future research directions in Section 5.

2. LITERATURE STUDY

Color, texture and shape features of an image have been used vastly in CBIR systems. Color is the most commonly used feature, and received most attention because it can be automatically extracted without human intervention and recently, there has been an increasing interest in studies relating to an integrated color and spatial retrieval approach (Goh and Tan, 2000). CBIR systems that combine color with texture features are also popular. The authors of Niblack *et al.* (1993), Pentland *et al.* (1994) and Stricker and Orengo (1995) combine local color features with texture, while (Carson *et al.* (2002) Chen and Wang (2002), Natsev *et al.* (1999) Li *et al.* (2000) combine global color features with texture. In Loupias and Sebe (2000), local color and texture features are computed on a window of regular geometrical shape surrounding the corner points. General purpose corner detectors are also used for this purpose (Harris and Stephens, 1988). Shape features have also been extensively used for retrieval systems (Gevers *et al.*, 1999; Jain and Vailalya, 1996). Fuzzy features were used to capture the shape information by Banerjee *et al.* (2004). Shape signatures are computed from blurred images and global invariant moments are computed as shape features.

Li *et al.* (2000) proposed a feature integrated region matching system which combines color features with wavelet coefficient and combines them with texture features for image retrieval. Bartolini *et al.* (2001) proposed a system called IRM, that uses a region-based feature selected based on color, texture, shape, and location properties for image retrieval. The IRM measure for evaluating overall similarity between images incorporates properties of all the regions in the images by a region-matching scheme. Compared with retrieval based on individual regions, the overall similarity approach reduces the influence of inaccurate segmentation, helps to clarify the semantics of a particular region, and enables a simple querying interface for region-based image retrieval systems.

Wavelet coefficients as texture features have also been used. Manjunath and Ma (1996) have used texture feature derived from Gabor wavelet coefficients. Do and Vetterli (2002) proposed wavelet based texture retrieval using generalized Gaussion density. Sastry and Ravindranath (2007) proposed a modified Gabor function for content based image retrieval. Han and Ma (2007) also proposed a rotation-invariant and scale invariant Gabor feature. The two methods both improve the retrieval speed at the cost of reducing the retrieval performance. Kokare and Biswas (2007) have used rotated discrete wavelet filters that are obtained by rotating the standard 2D-DWT filters (RWF). Computational complexity is same as that of the standard 2D-DWT filters decomposition, if both are implemented in 2D frequency domain.

From the literature study, it is evident that in CBIR, local features play a significant role in determining the similarity of images, along with the shape information of the objects. Wavelet variant feature selection algorithms have also gained equal popularity. Hence, in this paper, all these features were selected.

3 PROPOSED METHOD

Fusion-SOM CBIR System consists of six components, namely, (i) Image Database (ii) Feature Extraction Block (iii) Indexing Block (iv) Feature Database (v) Search and Retrieval Block (vi) User Interface. The process is shown in Figure 1.

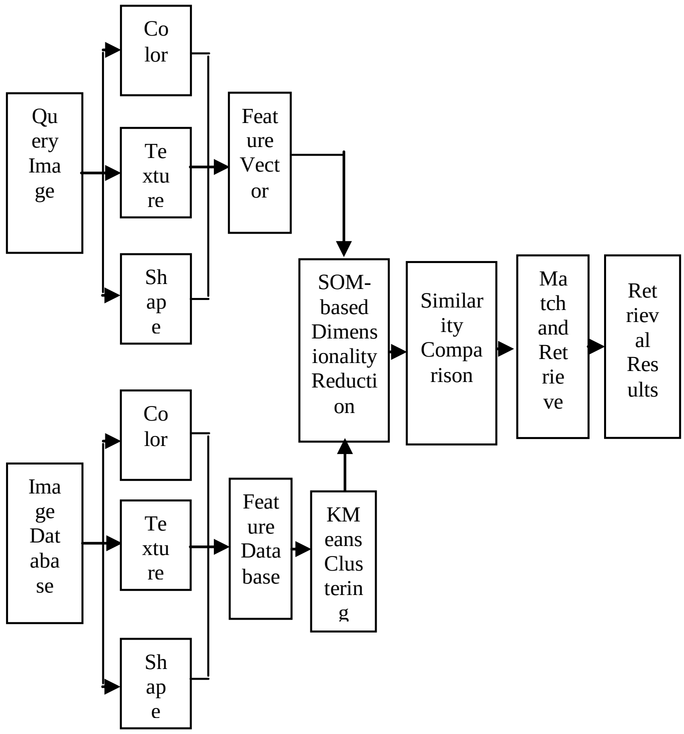

Figure 1 : CBIR System Framework

The image database contains the raw images, from which three descriptors that best describe them are retrieved by the feature extraction block. The three selected descriptors are color, texture and shape. These descriptors are termed as Feature Vectors. The feature vectors are used to classify images into predefined classes by the indexing component of CBIR system. The classified feature vectors now form the feature database. When a user presents a query, the features of the query image is extracted and the search and retrieval block searches the feature database to find a group that best matches the query feature vector. The user interface component displays these images as query result to the user.

The method used for extracting color features and dimensionality reduction is the same as the one proposed in Priya and Vasantha Kalyani David (2010). The method of extracting texture and shape features is explained below. To extract texture features, the standard DWT method was combined with Rotated Wavelet Filter (RWF) features and dual tree complex wavelet transform (DT-CWT) as proposed by Wu *et al.* (2010) is used. For each sub band, four texture features are calculated. They are energy, entropy, contrast and homogeneity (Equations 1-4)

$$\text{Entropy} = \sum_i \sum_j Co(i, j) \log Co(i, j) \quad (1)$$

$$\text{Energy} = \sum_i \sum_j Co^2(i, j) \quad (2)$$

$$\text{Contrast} = \sum_i \sum_j (i - j)^2 Co(i, j) \quad (3)$$

$$\text{Homogeneity} = \sum_i \sum_j \frac{Co(i, j)}{1 + |i - j|} \quad (4)$$

Where Co(i, j) is the co-occurrence matrix and is computed for several values of displacements and the one which maximizes the statistical measure is used. The co-variance matrix and displacements are calculated for each color sub band and are used. The average value is used as the final texture feature set for an image.

For extracting shape features, active contour model (Kass *et al.*, 1988) is used to detect the various regions of an image and the shape features are retrieved using the method proposed by Lin *et al.* (2004). The algorithm for feature level fusion, dimensionality reduction and matching process is given below.

Let C be the set of color features, T be the set of texture features and S be the set of shape features. Let R be the resultant feature vector after concatenating C, T and S. The average of all the respective features over the entire database is used to normalize the individual feature components. Let the normalized vectors be C', T' and S'. To avoid the curse of dimensionality, a k-means clustering algorithm is used. The k-means algorithm performs a two step procedure, where the first step removes redundant features and the second step retains points and removes points that are very near to the specific point. These points are removed because they may not provide additional information because of being in vicinity. The distance classifier used is Euclidean distance and the number of clusters is determined using the PBM cluster validity index (Pakhira *et al.*, 2004). To further select optimum feature vector, the SOM method proposed in Priya and Vasantha kalyani David (2010) is used.

If R' be the dimensionality reduced feature database and R" is the feature vector obtained from query image, then the retrieval system is based on a similarity measure defined between R' and R". Feature matching is performed using point pattern matching algorithm. This algorithm considers two points as matching if and only if, the spatial distance, directional distance and Euclidean distance between the corresponding features are within a threshold (Th) and each feature R" and R' contain (c, t, s, θ, feature) (c, t, s features

belonging to different feature vectors). This means that a point in R" is said to be a match with R', if the spatial distance (SD) between them is smaller than a given tolerance Th_1, the difference direction (DD) between them is smaller than an angular tolerance Th_2 and the Euclidean difference (ED) between them is between some threshold. To further improve the accuracy of the formulas, weights W_i is attached to each of the feature vectors. The weight is calculated as $W_i = \frac{1}{1+\sigma_i}$ where σ is the standard deviation of the ith feature of the image. The distance Equations (5) – (7) used for this purpose are given below .

$$SD(R', R'') = \sqrt{W_c * |c'' - c'|^2 + W_t\, |t'' - t'|^2 + W_s\, |s'' - s'|^2} \le Th_1 \quad (5)$$

$$DD(R', R'') = \min(|\theta'' - \theta'|, 360° - |\theta'' - \theta'|) \le Th_2 \quad (6)$$

$$ED(R', R'') = \sqrt{\sum |f'' - f'|} \le Th_3 \quad (7)$$

where f is the feature

$$\text{Matching Score} = \frac{100 x Q^2}{M x N} \quad (8)$$

The final matching score for the ED and point pattern matching technique is based on the number of matched pairs found in the two sets, and is computed using Equation 8.

where Q is the number of paired points between the database and the query concatenated point sets, while M and N are the number of points in R' and R" respectively. The top ‘n’ closest images are taken as query result, excluding the query image present in the database.

4. EXPERIMENTAL RESULTS

The image database used during experimentation consists of 650 JPEG color images randomly selected from the World Wide Web. Figure 2 depicts a sample of images in the database. During testing, care was taken to choose a query image from different types of images like same scene, large change in appearance, etc. The performance metrics used during evaluation is the precision-recall measure and retrieval time. Precision is defined as the fraction of retrieved images that are truly relevant to the query image and recall is defined as the fraction of relevant images that are actually retrieved. Retrieval time is the time taken to retrieve images after giving the query image. The system was developed in MATLAB 7.3 and all the experiments were conducted in Pentium IV machine with 512 MB RAM. The histograms for all the images were constructed using 72 color bins after converting the RGB color space to HSV colour spam. The experimental results of the proposed Fusion-SOM CBIR System are compared with its base system SOM-Color CBIR [***].

Figure 2 : Sample Images from test database

Figure 3 shows the precision-recall values obtained during experimentation.

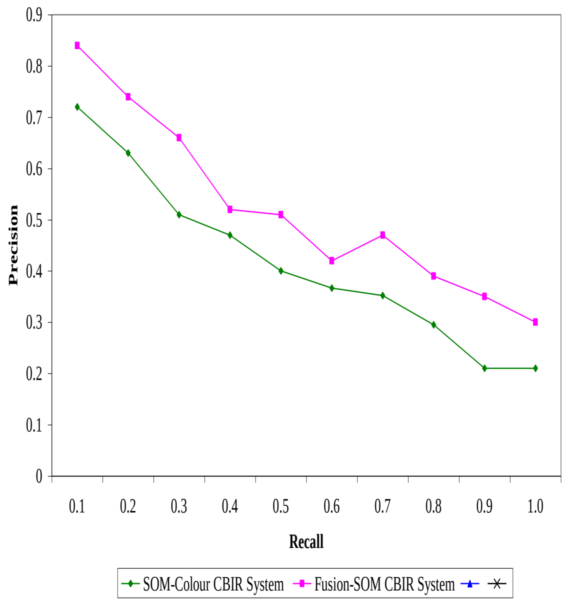

Figure 3 : Precision and Recall

From the figure, it could be seen that the proposed method is an improved version of the base system using SOM and histogram. The results prove that combination of various features improves the image retrieval process. The image retrieval time of Fusion-SOM CBIR System was 1.43 seconds and that of SOM-color CBIR System was 1.67 seconds. Thus, the proposed method shows a speed efficiency of 14.37%. This shows that the dimensionality reduction in both cases is excellent.

5. CONCLUSION

In this paper, a model that used multiple features for content based image retrieval is proposed. The proposed system used color features, texture features and shape features which were fused to obtain feature vector. A k-means clustering algorithm and SOM based dimensionality reduction techniques are used. A similarity measure that combines spatial distance, direction distance and Euclidean distance is used. Several experiments were performed to analyze the performance of the proposed system. The results proved that the combination method is efficient in terms of precision, recall and speed of image retrieval. The work can be extended to use more local and global image features along with region-based or partitioning feature selection algorithms and their effect on retrieval performance can be analyzed. Multiple query images can also be considered. Further, the present CBIR system can also be integrated with machine learning classifiers to further improve their performance.

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