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Efficient Re-Ranking and Image Retrieval Based on Fuzzy Color Feature Extraction

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Abstract: Image retrieval is an emerging research area for a multimedia database. The existing EMR is taking more time for the large database. Retrieval of images based on color features such as Color, texture and shape have demonstrated to have its own set of limitations under different conditions. Proposed fuzzy based methods for Content-based image retrieval System, they are precision, recall and accuracy value for indexing the Visual words and fuzzy color and texture Histogram. Images were represented by low-level features and it is important to reduce semantic gap between high-level and low-level features of images to retrieve visual similar images and re-ranking of images. It proposes a latent semantic indexing (LSI) method to re-rank images that are retrieved using image retrieval method. Color based K-means clustering algorithm performed calculation of the dissimilarity. The color extraction of an image includes feature description, index generation and similarity match. Implemented and tested process was based on three parameters like precision value, recall value and Accuracy rate. Based on the Experimental results FCTH (Fuzzy Color and Texture Histogram) method is more efficient when comparing with other methods.

Key words: Content Based Image Retrieval · Image indexing · Fuzzy Color histogram · Edge Directive Descriptors · Similarity measurement

INTRODUCTION

The growth of digital images through the extensive popularization of computers and the Internet makes the development of efficient image retrieval technique imperative. Content-based image retrieval, known as CBIR [1], undertakes the retrieval procedure. The color image content of the images is mapping into a new space, named the feature space. The features have to be discriminative and enough for the description of the objects. Basically, The key to reaching a successful retrieval system is to choose the right descriptors that represent the images as "strong" and unique as possible. Concerning their type, CBIR systems can be classified in systems that use color information, those that use texture information and finally in systems that use shape information. It is very difficult to achieve satisfactory retrieval results by using only one of these feature categories.

In most retrieval systems that combine two or more feature types, such as color and texture, independent vectors are used to describe each kind of information. It is possible to achieve very good retrieval scores by increasing the size of the descriptors, but this technique has several drawbacks. If the descriptor has hundreds or even thousands of bins, it may be of no practical use because the retrieval procedure is significantly delayed.

Propose a new low-level descriptor that includes in one quantized histogram color and texture information. This feature (FCTH) results from the combination of 3 fuzzy units. Initially, the image is segmented into a preset number of blocks. Each block passes successively from all the fuzzy units. In the first unit, a set of fuzzy rules undertakes the extraction of a Fuzzy-Linking histogram. This histogram stems from the HSV color space. Twenty rules are applied in a three-input fuzzy system in to generate eventually a 10-bin histogram. Each bin corresponds to a preset color.

The second value, a two-input fuzzy system, to expand the 10-bins histogram into the 24-bins histogram, importing thus information related to the hue of each color that is presented. Next, in the third unit, each image block is transformed with Haar Wavelet transform and a set of texture elements are exported. These elements are used as inputs in a third fuzzy system which converts the 24-bins histogram in a 192-bins histogram, importing texture information in the proposed feature. In this unit, eight

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rules are applied in a three-input fuzzy system. The process is described with a similarity metric that can be used to calculate the distance of images according to the proposed feature.

Related Work: In a typical CBIR system, each image can be represented using features such as colour, texture or shape. For example, the purpose color model or color space is facilitate the management of color features in some specific order. It is a specification of a coordinate system and a subspace within that system [2]. In terms of human observation, it is nature to define a color by its attributes of brightness, hue and color fullness. For computer graphics applications, it might easier to describe a color using the amounts of red, green and blue. In this research, the system converts RGB to HSV due to the advantages of HSV in representing colors in the way they are perceived. As shown in Figure 1, the HSV colour space can be considered as a cone with its apex pointing downward. Hue is defined as an angle moving around the color circle shown at the top edge of cone.

The Color is an expressive visual attribute that can provide more information about the visual content of an image. Color space facilitates the specification of color which defines the particular color feature. Each color in the color space is a single point represented in a coordinate system. Most widely used color spaces are RGB, LUV, HSV and HMMD [4, 5]. RGB color space is most commonly used for image display which is composed of Red Green Blue color components. HSV space is used in computer graphics to describing color with the color components as hue, saturation (lightness) and value (brightness). CMY color space mainly used for printing. It consists of cyan, magenta and yellow color components.

Manifold Ranking (MR) [6, 7] a famous graph-based ranking model, ranks data samples with on the intrinsic geometrical structure collectively revealed by a large number of data. It is exactly in line with our consideration. The score is treated as a similarity metric defined on the manifold, which is more meaningful to capturing the semantic relevance degree. Firstly applied MR to CBIR and significantly improved image retrieval performance compared with state-of-the-art algorithms.

Manifold ranking is unacceptable to re-compute the model for a new query. That means, an original manifold ranking is inadequate for a real world CBIR system, in which the user provided query is always an out-of-sample.

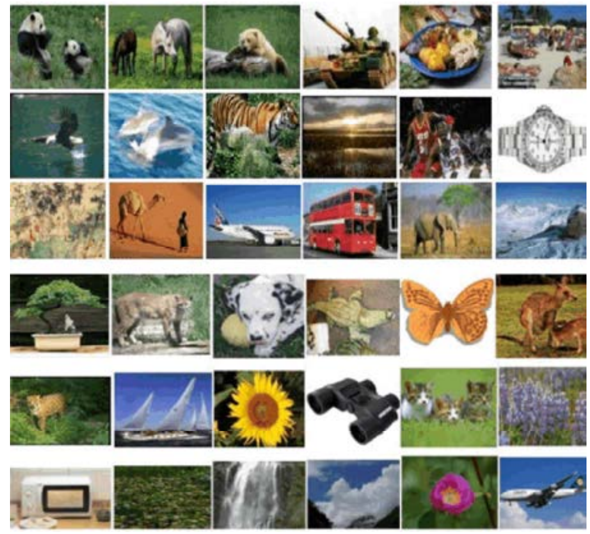

Fig. 1: Some Sample Images from the Database

Specifically, we divide the image space into non-overlapping square image-blocks and then extract the edge information from them.

Existing Efficient Manifold Ranking algorithm which extends the original manifold ranking to handle large scale databases.EMR tries to address the shortcomings of original manifold ranking from two perspectives: the first is scalable graph construction; and the second is the efficient computation, especially for out-of-sample retrieval.

Proposed Approach: ontent-based image retrieval [11] is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content based means that the search makes use of the contents of the images themselves, rather than relying on human-input metadata such as captions or keywords. A content-based image retrieval system (CBIR) is a piece of software that implements CBIR.

In CBIR [11] each image that is stored in the database has its features extracted and compared to the features of the query image. It involves two steps.

Feature Extraction: The first step in this process is to extract the image features to a distinguishable extent.

Matching: The second step involves matching these features to yield a result that is visually similar.

Indexing: Indexing [11] is done using an implementation of the Document Builder interface. A simple approach is to use the Document Builder Factory, which creates

Document Builder instances for all available features as well as popular combinations of features. A Document Builder is basically a wrapper for image features creating a Lucene Document from a Java Buffered Image. The signatures or vectors extracted by the feature implementations are wrapped in the documents as text. The document output by a Document Builder can be added to an index.

Fuzzy Color and Texture Histogram: CTH [11] is a new low-level descriptor includes in one quantized histogram color and texture information. This features result which forms the combination of three fuzzy units. Initially the image is segmented in a preset number of blocks. Each block passes through all the fuzzy units.

The first unit [11], extract the fuzzy linking histogram by using a set of fuzzy rules. This histogram stems from the HSV color space. In a three input fuzzy system, twenty rules are applied in order to generate a 10-bin Histogram, each bin corresponds to a preset color.

In the second unit [10], this paper proposes a two input fuzzy system, in order to expand the 10-bin histogram into 24-bin histogram. Thus the information related to the hue of each color is presented.

In the third unit [11], each image block is transformed to the Haar wavelet transform and a set of a texture elements are exported. These elements are given to an input of third fuzzy system, which converts 24-bin histogram into a 192-bin histogram, importing texture information in the proposed feature. In this unit eight rules are applied in a three input fuzzy system. By using the Gustafson kessel [9] fuzzy classifier, 8-regions are shaped which are used to quantize the values of the 192 FCTH factors in the interval 1to7, limiting the length of the descriptor in 576 bits per image.

Fuzzy Color Segmentation: A fuzzy system was proposed in order to produce a fuzzy-linking histogram, which regards the three channels of HSV as inputs and forms a 10 bins histogram as an output. Each bin represents a preset color as follows: (0) Black, (1) Gray, (2) White, (3) Red, (4) Orange, (5) Yellow, (6) Green, (7) Cyan, (8) Blue and (9) Magenta. These colors were selected based on works that had presented in the past.

The improved by recalculating the input membership value limits and resulting to a better mapping in the 10 custom colors. These new limits are calculated based on the position of the vertical edges of images that represent the channels H (Hue), S (Saturation) and V (Value). The vertical edges [11] of the channel H, which were used for determining the position of member ship values. The membership values limits of S and V are identified with the same process. The use of coordinate logic filters (CLF) is found to be the most appropriate among other edge detection techniques for determining the fine differences and finally extracting these vertical edges. In the procedure followed, each pixel is replaced by the result of the coordinate logic filter “AND” operation on its 3 × 3 neighborhood. The result of this action, stresses the edges of the image. Receiving the difference between the initial and the filtered image, the total of edges is exported.

Channel S is divided in 2 fuzzy areas. This channel defines the shade of a color based on white. The first area, in combination with the fuzzy area that is activated in channel V, is used to define if the color is clear enough to be ranked in one of the categories which are described in H histogram, or if it is a shade of white or gray color. The third input [10], channel V, is divided in 3 areas. The first one is actually defining substantially when the input will be black, independently from the values that gives to the other inputs. The second fuzzy area, in combination with the value of channel S gives the gray color.

A set of 20 TSK-like rules with fuzzy antecedents and crisp consequents [13] have been used. In the consequent part there are actually the variables that count the number of the original image blocks, which are mapped to each specific bin of the 10 bin histogram. Four of the rules depend on two only inputs (S and V). For these rules the decision is independent from the H value. The design of a system that approaches these shades is based on the determinations of the subtle vertical edges appearing in images with smooth transition from the absolute white to the absolute black through a color. The use of coordinate logic filters (CLF) “AND” is found to be appropriate for determining these vertical edges too.

The values of S and V [11] from each block as well as the value of the bin (or the bins) resulting from the fuzzy 10-bins unit constitute entries in the 24-bins Fuzzy Linking system. The second system inputs are analyzed as follows. Channel S as well as channel V is divided in two fuzzy regions. This system actually undertakes to classify the input block in one (or more) from the three hue areas derived after the vertical edge extraction procedure described above. These hues are labeled as follows: Dark Color.

Fuzzy Texture Segmentation: The fuzzy color texture information [11] from the images, three features that represent energy in high frequency bands of wavelet transforms were used. These elements are the square root of the second order moment of wavelet coefficients in high frequency bands. To obtain these features, the Haar transform applied to the Y (Luminosity - that emanates from the YIQ color space) component of an image block. The derision of the block size depends on the image dimensions and is described in the following section. Suppose for example that the block size is 4 × 4. After a one-level wavelet transform, each block is decomposed into four frequency bands. Each band contains 2 × 2 coefficients. The coefficients in the HL band are {Ckl , Ck, l+1 , Ck+1, l , Ck+1, l+1}.

The other two features are computed similarly from the LH and HH bands. The motivation for using these features is their reflection of texture properties. Moments of wavelet coefficients in various frequency bands have proven effective for discerning texture. The intuition behind this is that coefficients in different frequency bands signal variations in different directions. For example, the HL band shows activities in the horizontal direction. An image with vertical strips thus has high energy in the HL band and low energy in the LH band. This texture feature is a good compromise between computational complexity and effectiveness.

Similarity Measure: Similarity measurement coefficient [13] is used to measure the color distance between the images in Fuzzy color and texture Histogram (FCTH) techniques.

$$T_{ij} = t(x_i, x_j) = \frac{x_i^T x_j}{x_i^T x_i + x_j^T x_j - x_i^T x_j}$$

where [13] xT is the transpose vector of x. In the absolute congruence of the vectors the Tanimoto coefficient takes the value 1, while in the maximum deviation the coefficient tends to zero.

Re-Ranking: An indexing and retrieval method [10] i.e. Latent semantic indexing (LSI) is used a mathematical method to recognize patterns in the associations among the concepts and terms enclosed in an object. LSI is based on principle that, words that are used in similar context tends to have similar meanings. LSI uses matrix evaluation to retrieve information to find similar images based on the underlying information.

Latent Semantic Indexing method [10] is used to perform re-ranking of retrieved images. LSI method applies synonymy concept to given query keyword and then compares it with title and description of images to produce resultant similarity value in fraction (percentage). By using this similarity co-efficient image is re-ranked.

Experimental Results and Discussion: The low-level feature extraction techniques [10] proposed are tested on Corel database. The query images used in this analysis belong to the major categories like Butterfly, Rose, Building, Tiles, Sunset, Horse, Hills, Flags, Trees and Car. The performance of each technique is measured by calculating its IRP and recall value as given in equation 2 and equation 3 respectively.

$$IRP = \frac{Number \quad of \quad relevent \quad images \quad retrieved}{Total \quad number \quad of \quad images \quad retrieved}$$

$$Recall = \frac{Number \quad of \quad relevent \quad images \quad retrieved}{No. \quad of \quad relevent \quad images \quad in \quad the \quad database}$$

The focus of all the CBIR techniques are mainly on the-low level image features like Color, Texture and Shape. Also it is found that the performance of the CBIR techniques is not consistently uniform for various categories of images. The detailed observations of performance of various CBIR techniques are listed in Table 1 [11].

Table 1 show the comparison of edge histogram EMR and Proposed system compared to two techniques the proposed fuzzy color extraction give high accuracy average.

Table 2 show the comparison of edge histogram EMR and Proposed system compared to two techniques the proposed fuzzy color extraction give high image retrieval precision.

The WANG database is a subset of thousand images of the Corel stock photo database which have been manually selected and which form ten classes of hundred images each. The WANG database can be considered similar to common stock photo retrieval tasks with several images from each category and a potential user having an image from a particular category and looking for similar images.

The ten classes are used for relevance estimation: given a query image, it is assumed that the user is searching for images from the same class and therefore the remaining ninety nine images from the same class are considered relevant and the images from all other classes are considered irrelevant.

The Fig. 3 show the image retrieval based on FCTH give high performance for the query image with fast image matching.

The Fig. 4 show the proposed FCTH give high IRP compared to existing system for color image.

Fig. 2: Query Image

Fig. 3: First 9 retrieved images from the database

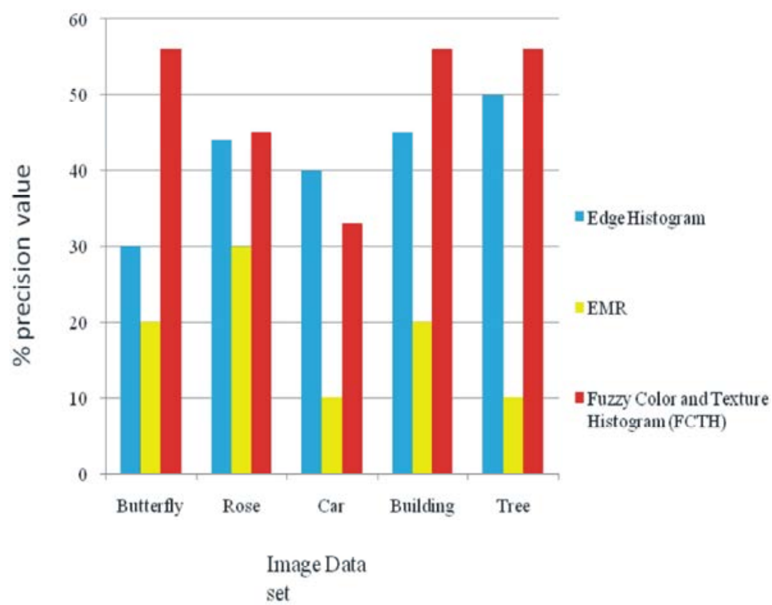

Fig. 4: Comparison chart for Existing and Proposed system

Table 1: Different type Query Image Category comparison

	Edge Histogram		EMR		Fuzzy Color and Texture Histogram	
Data Set	IRP	Recall	IRP	Recall	IRP	Recall
Butterfly	33	30	45	40	56	50
Sunrise	22	20	67	60	56	50
Rose	67	60	45	40	45	40
Car	45	40	67	60	33	30
Building	78	70	67	60	56	50
Flag	11	10	67	60	78	70
Tree	56	50	67	60	56	50
Average	46	40	61	54	54	56

Table 2: Comparison of Existing Feature Extraction Technique with proposed system

	% Image Retrieval Precision value for Existing System		% Image Retrieval Precision value for Proposed system
Query image category	Edge Histogram	EMR	Fuzzy Color and Texture Histogram(FCTH)
Butterfly	30	20	56
Rose	44	30	45
Car	40	10	33
Building	45	20	56
Tree	50	10	56
Average IRP value	40	20	49

CONCLUSION

The extraction of a new low-level feature [11] that contains, in one histogram, color and texture information and an extension of this feature so as to incorporate spatial information. This element is intended for use in image retrieval and image indexing systems. Experimental results show that the proposed feature can contribute in accurate image retrieval. Its main functionality is image-to-image matching and its intended use is for still-image retrieval, where an image may consist of either a single rectangular frame or arbitrarily shaped, possibly disconnected, regions. The increase of texture regions would definitely help in the improvement of the results but also in the use of FCTH for semantics image retrieval.

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