ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

Efficient Image Retrieval Based on Fuzzy Color Feature Extraction

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Abstract: Image retrieval is an emerging research area for multimedia database. It is the basic requirement task in the present scenario. Retrieval of images based on visual features such as color, texture and shape have proven to have its own set of limitations under different conditions. This paper experiments various methods available for Content based image retrieval System, they are precision, recall and accuracy value for Bag of Visual words, Color and Edge Directive Descriptors, Fuzzy Color and Texture Histogram. The Extraction of an image includes feature description, index generation and feature detection. The methods are implemented and tested based on three parameters like precision value, recall value and Accuracy rate. The Experimental results show that FCTH (Fuzzy Color and Texture Histogram) method is more efficient when comparing with other methods.

Keywords: Content Based Image Retrieval; Fuzzy Color histogram; Edge Directive Descriptors; Similarity measure.

I. INTRODUCTION

The rapid growth of digital images through the widespread 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 visual content of the images is mapped into a new space, named the feature space. The features have to be discriminative and sufficient for the description of the objects. Basically, the key to attain a successful retrieval system is to choose the right descriptors that represent the images as "strong" and unique as possible. Regarding 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. Also, increasing the size of the descriptor increases the storage requirements which may have a significant penalty for databases that contain millions of images. Many presented methods limit the length of the descriptor to a small number of bins, leaving the possible factor values in decimal, non-quantized form.

This paper proposes 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 in a preset number of blocks. Each block passes successively from all the fuzzy units. In the first unit, a set of fuzzy rules undertake 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 order to generate eventually a 10-bin histogram. Each bin corresponds to a preset color.

As second unit, this paper proposes a two-input fuzzy system, in order to expand the 10-bins histogram into 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 rules are applied in a three-input fuzzy system.

The process is described with a similarity metric that can be used in order to calculate the distance of images according to the proposed feature.

II. RELATED WORK

In a typical CBIR system, each image can be represented using features such as colour, texture or shape. For example, the purpose of a color model or colour space is to facilitate the management of colour features in some specific order. It is a specification of a coordinate system and a subspace within that system where each colour is introduced by a single point [2]. There are many well-studied and applied colour systems such as RGB

 DOI 10.17148/IJARCCE.2015.49121

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

(Red, Green, Blue), HLS (Hue, Lightness, Saturation) and HSV (Hue, saturation, Value) [3] . In terms of human observation, it is nature to define a colour by its attributes of brightness, hue and color fullness. For computer graphics applications, it might be easier to describe a colour 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 colours 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. It is viewed from the circular side of the cone; Hue is defined as an angle moving around the colour circle shown at the top edge of cone.

Color is an expressive visual attributes that can provide more information about the visual content of an image. Color space facilitates the specification of color which defines 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 respect to 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.

However, manifold ranking has its own drawbacks to handle large scale databases – it has expensive computational cost, both in graph construction and ranking computation stages. Particularly, it is unknown how to handle an out-of-sample query (a new sample) efficiently under the existing framework. It is unacceptable to re-compute the model for a new query. That means, original manifold ranking is inadequate for a real world CBIR system, in which the user provided query is always an out-of-sample.

III.PROPOSED APPROACH

Content-based image retrieval, also known as query by image content and content-based visual information retrieval 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 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.

A. *Indexing*

Indexing 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 (e.g. all MPEG-7 features or all available 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.

B. *Fuzzy Color and Texture Histogram*

FCTH 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 the entire fuzzy units. The first unit, 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, 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, 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 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.

b1. *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.

 DOI 10.17148/IJARCCE.2015.49121

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
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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 of the channel H, which were used for determining the position of membership 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, 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 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 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 analysed as follows. Channel S as well as channel V is divided in 2 fuzzy regions. This system actually undertakes to classify the input block in one (or more) from the 3 hue areas derived after the vertical edge extraction procedure described above. These hues are labelled as follows: Dark Color (as Color is used the color that attributed by the first 10-Bins system) - Color and Light Color.

b2. *Fuzzy Texture Segmentation*

The texture information 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 $\{C_{kl}, C_{k,l+1}, C_{k+1,l}, C_{k+1,l+1}\}$. 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.

C. Similarity Measure

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

$$T_{ij} = t(x_i, x_j) = \frac{x_i^T x_j}{x_i^T x_i + x_j^T x_j - x_i^T x_j} \quad (1)$$

Where x^T 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.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The low level feature extraction techniques proposed in this paper 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.

$$\mathrm{IRP} = \frac{\text{Number of relevent images retrieved}}{\text{Total number of images retrieved}} \times 100 \quad (2)$$

$$\mathrm{Recall} = \frac{\text{Number of relevent images retrieved}}{\text{no of relevent image in the database}} \quad (3)$$

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.

FIG. 1 QUERY IMAGE

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
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Fig. 2 Some Sample Images from the Database

TABLE I: COMPARISON OF DIFFERENT TECHNIQUES WITH QUERY IMAGE

Data Set	Edge Histogram		EMR		Fuzzy Color and Texture Histogram	
Query image	IRP	Recall	IRP	Recall	IRP	Reca ll
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	**60**
Average IRP value	46	40	61	54	54	55

Table 1 show the different query image compare with different feature extraction techniques ht proposed system give high irp rate.

TABLE III: COMPARISON OF DIFFERENT TECHNIQUES WITH PRECISION

Data set	% Image Retrieval Precision value			
Query image category	**Color Layout**	**Edge Histogram**	**EMR**	**Fuzzy Color and Texture Histogram (FCTH)**
Butterfly	0.32	0.32	0.61	0.73
Rose	0.45	0.54	0.67	0.84
Car	0.34	0.43	0.72	0.82
Building	0.42	0.48	0.63	0.86
Tree	0.37	0.47	0.62	**0.85**
% precision	0.38	0.44	0.65	0.828

Table 2 show the proposed techniques are compared with the existing Technique, EMR and FCTH Image Retrieval Precision value has improved.

The fig 3 shows the performance comparison with exiting using % precision value FCTH high precision.

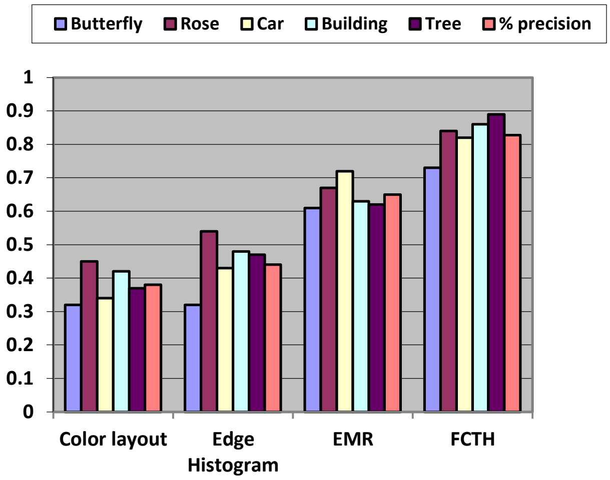

Fig. 3 Comparison of feature extraction technique with precision

For example IRP Calculation

$$IRP = \frac{12}{20} \times 100 = 60$$

For example Precision Calculation

$$Precision = \frac{17}{20} = 0.85$$

V. CONCLUSION

This paper presents the extraction of a new low level feature 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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DOI 10.17148/IJARCCE.2015.49121

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ISSN (Print) 2319-5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 9, September 2015

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