Efficient Color and Texture Feature Extraction Technique for Content Based Image Retrieval System

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Abstract: *The future user needs in the field of multimedia retrieval is the focus of many research and development activists. It is empirically observed that no single algorithm is efficient in extracting all different types of images like building images, flower images, car images and so on. Hence, a thorough analysis of certain color, texture and shape extraction techniques are carried out to identify an efficient Content Based Image Retrieval (CBIR) technique which suits for a particular type of images. The extraction of an image includes feature description, index generation and feature detection. The low-level feature extraction techniques are proposed in this paper are tested on Corel database, which contains 1000 images. The feature vectors of the Query Image (QI) are compared with feature vectors of the database images to obtain Matching Images (MI). This paper proposes Fuzzy Color and Texture Histogram (FCTH), and Color and Edge Directivity Descriptor (CEDD) techniques which extract the matching image based on the similarity of color and edge of an image in the database. The Image Retrieval Precision value (IRP) of the proposed techniques are calculated and compared with that of the existing techniques. The algorithms used in this paper are Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and Fuzzy linking algorithm. The proposed technique results in the improvement of the average precision value. Also FCTH and CEDD are effective and efficient for image indexing and image retrieval.*

Keywords: *CBIR, IRP, FCTH, CEDD.*

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1. Introduction

Content Based Image Retrieval (CBIR) systems are based on color, texture, shape and edge information are available in the literature. The general applications of CBIR are consumer digital photo album, digital museum, Moving Picture Experts Group (MPEG-7) content descriptor, general image collection for licensing and natural collections. This paper describes an image retrieval technique based on multi wavelet texture features. Texture is an important feature of natural images. Features of an image should have a strong relationship with semantic meaning of the image. CBIR system retrieves the relevant images from the image data base for the given Query Image (QI), by comparing the feature of the QI. Edges in an image constitute an important feature to represent their content of the image. Human eyes are very sensitive to edge features for image perception. Histogram is used to represent an important edge feature. An edge histogram in an image space represents the directionality of the brightness changes and its frequency. The normative MPEG-7 edge histogram is designed to contain the 80 bins of local edge distribution. These 80 bin histograms are the standardized semantics for MPEG-7 Edge Histogram Descriptor (EHD). The local histogram bins are not sufficient to represent global features of the edge distribution. The global edge distribution is needed to improve the retrieval performance of an image and images in the database. Relevant images are retrieved according to minimum distance or maximum similarity measure calculated between features of QI and every image in an image database. CBIR systems are based on many features such as texture, color, shape and edge information. Texture contains important information about the structural arrangement of surfaces and their relationship to the surroundings. Varieties of techniques are developed for texture analysis. Most of the texture features are obtained from the application of a local operator, statistical analysis [14] or measurement in transform domain.

2. Previous Works

An image can be represented as a set of low level visual features such as color, texture and shape features. This work extracts the color and texture feature of an image in a database. Feature selection algorithm is based on a fuzzy approach and relevance feedback. The discrete image transforms are used for image data compression and energy compaction. The energy level in the image depends on level of colors used. Two discrete image transforms are used in this paper namely Discrete Hadamard Transform (DHT) and Discrete Wavelet Transform (DWT) [4]. These two transforms are applied to different color models namely Hue, Saturation and Value (HSV) and Y′ is the luma component and Cb and Cr are the blue-difference and red-difference chroma components (YCbCr) separately in a given large standard database with 1000 images formed from 10 different classes taken from the Corel collection.

The second-order Local Tetra Pattern (LTrP) that is calculated based on the direction of pixels using horizontal and vertical derivatives. The proposed method is different from the existing Local Derivative Pattern (LDP) in a manner that it makes to use of 0° and 90° derivatives of LDPs for further calculating the directionality of each pixel. The performance resulting from the combination of the Gabur Transform (GT) and the LTrP [2] have been also analyzed, because it is reasonable to assume that low-level visual features are sampled from a low dimensional manifold and embedded in a high dimensional space. Hence, the Biased Discriminate Euclidean Embedding (BDEE) [5] and its semi-supervised extension to map high-dimensional samples to a low-dimensional space are proposed. BDEE precisely preserves both the intra-class geometry and interclass discrimination.

In-plane rotation and scale invariant features [6] of images in the radon transform domain. The initial dictionaries are learned through initial clusters that are determined using the hamming distance between nearest-neighbor sets of each feature pair.

Previous work CBIR is utilized through calculating some of the primitive color features. The indexing of the image database is performed with Self-Organizing Map (SOM) which identified the best matching units. Fuzzy color histogram [3] and subtractive fuzzy clustering algorithms have been utilized to identify the cluster for which the QI belonging. This approach only focus the primitive color features.

Clustering algorithms have been developed previously which includes fuzzy means. This class of algorithms is generalized to include the fuzzy co-variances [9, 15]. The resulting algorithm closely resembles maximum likelihood estimation of mixture densities. It is argued that use of fuzzy co-variances is a natural approach to fuzzy clustering [1]. Experimental results are presented which indicate that more accurate clustering may be obtained by using fuzzy co-variances.

Co-ordinate logic filters [13], execute co-ordinate logic operations among the pixels of the image. These filters are very efficient in various 1D, 2D, or higher-dimensional digital signal processing applications, such as noise removal, magnification, opening, closing, skeletonization and coding, as well as in edge detection, feature extraction, and fractal modeling. Images of any given concept are regarded as instances of a stochastic process that characterizes the concept. The experimental implementation, focus on a particular group of stochastic processes that is the Two-Dimensional Multi resolution Hidden Markov Models (2D MHMMs). Query refinement based on relevance feedback, suffer from slow convergence and do not guarantee to find intended targets [12].

The feature extraction techniques in the existing systems are:

- Color Layout Descriptor (CLD) extraction
- Scalable Color Descriptor (SCD) extraction
- Edge Histogram Descriptor (EHD) extraction
- Auto color correlogram extraction.

2.1. CLD Extraction

In CLD [14] extraction process, the image consists of three color channels like R, G and B, which can be transformed into YCbCr color space. Each color space will be again transformed by 8x8 Discrete Cosine Transform (DCT) matrices of coefficients, to obtain three 8x8 DCT matrices [10, 7]. The CLD descriptor was generated by reading in zigzag order, six coefficients from the Y DCT matrix and three coefficients from each DCT matrix of the two chrominance components. The descriptor is saved as an array of 12 values.

2.2. SCD Extraction

The SCD extracts a quantized HSV color of the histogram from a given image of RGB format. The probability values of each bin are calculated and indexed. The resulting histogram is transformed into discrete Haar transformation which can be represented in MPEG-7 standard. The non-uniform quantized array of values sorted.

2.3. EHD Extraction

In EHD Extraction, the image space divided into a fixed number of image blocks. In this method to extract the edge features, the image block is applied to digital filters in the spatial domain. First, divide the image block into four sub blocks as assigning labels from 0 to 3. The four sub blocks represent the average gray levels at $(i, j)^{th}$ image block respectively. Also, this method can represent the filter coefficients for vertical, horizontal, 45 degree diagonal, 135 degree diagonal and non directional edges of an image as $f_v(k)$, $f_h(k)$, $f_{d\ 45}(k)$, $f_{d\ 135}(k)$, and $f_{nd}(k)$, respectively, where k=0, …, 3 represents the location of the sub blocks. The respective edge magnitudes are $m_v(i, j)$, $m_h(i, j)$, $m_{d\ 45}(i, j)$, $m_{d\ 135}(i, j)$, and $m_{nd}(i, j)$ for the $(i, j)^{th}$ image block. This method recommended for the MPEG-7 standard.

2.4. Auto Color Correlogram Extraction

The highlights of these features are: It includes the spatial correlation of colors, it can be used to describe the global distribution of local spatial correlation of colors, it is easy to compute and the size of the feature is fairly small. To compare the feature vectors by using different distance measure. The L1 distance measure is used commonly to compare the component wise difference between vectors. The distance measure is used to calculate the relative differences. In most cases it performs better than the absolute measure. A color correlogram expresses how the spatial correlation of color changes in pairs with distance. A color histogram captures only the color distribution in an image and does not include any spatial correlation information.

2.5. Paper Outline

In this paper, new approach for texture and shape based image retrieval based on new indexing structure and feature extraction techniques are presented. The rest of the paper is organized as follows. Section 3 is on overview of proposed approach, indexing and feature extraction. Section 4 is implementation and section 5 is the similarity measure performance evaluation. Section 6 is experimental results. Finally, the conclusion is drawn in section 7.

3. Proposed Approach

The proposed approaches are explained as follows.

3.1. 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.

3.2. Fuzzy Color and Texture Histogram

Fuzzy Color and Texture Histogram (FCTH) is a new low level descriptor includes in one quantized histogram color [8] 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, 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. Figure 1 show that FCTH extraction.

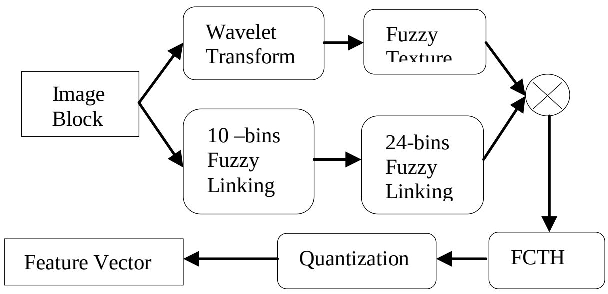

Figure 1. FCTH extraction.

3.3. Color and Edge Directivity Descriptor

A new low-level feature that combines color and texture information in one histogram and its length does not exceed 54 bytes. First the image is separated in a preset number of blocks. In order to extract the color information, a set of fuzzy rules are used to undertake the extraction of a fuzzy linking histogram that was proposed. This histogram stems from the HSV color space. Twenty rules are applied to a three input fuzzy system that generates a 10-bin quantized histogram. Each bin corresponds to a preset color. The number of blocks assigned to each bin is stored in a feature vector. Figure 2 show that Color and Edge Directivity Descriptor (CEDD) Extraction.

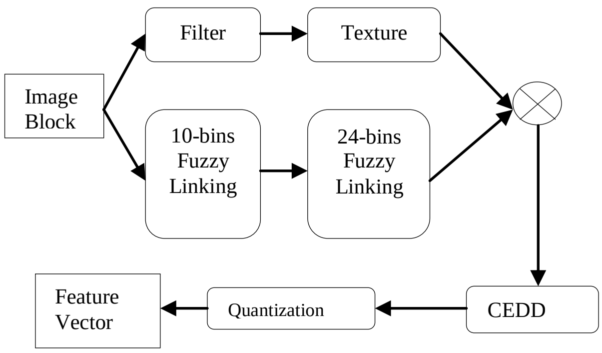

Figure 2. CEDD extraction.

Then the four extra rules are applied to a two input fuzzy system, in order to change the 10-bins histogram into 24-bins histogram, importing the information related to the hue of each color presented. The five digital filters are proposed in the MPEG-7 EHD is also used for exporting the information related to the texture of the image. Each image block is classified into one or more of the six texture regions that has been fixed and shaping the 144-bins histogram. The Gustafsan Kessel classifier is used to shape the eight regions which are used to quantize the values of 144 CEDD factors in the interval 0 to 7, limiting the length of the descriptor in 432-bits.

The CEDD unit associated with color and texture unit. The color unit extracts the color information and the texture unit extracts the texture information.

The CEDD histogram is constituted by six regions that can be determined by the texture unit. Each region is constituted by 24 individual regions, emanating from the color unit. The final histogram includes 6*24=144 regions. In order to shape the histogram, first the image is separated into 1600 image blocks. Each image block feeds successively all the units. If the bin is defined that results from the texture unit as N and the bin that results from the color unit as M, then the image block is placed in the output histogram position as N*24+M.

In the Texture unit, the image block is separated into four regions of sub blocks, the value of each sub block is the mean value of the luminosity of the pixels that participate in it. The luminosity values are derived from the transformation the Y component represents the luma information, I and Q represent the chrominance information (YIQ) color space.

In the color unit, every image is transported in the HSV color space. The mean values of H, S and V are calculated and they constitute the inputs of the fuzzy system that shapes the fuzzy 10-bins histogram. Assume that the classification resulted in the fourth bin, which dictates the color. Then the second fuzzy system in 24-bin fuzzy linking, using the mean values of S and V, calculate the hue of the color and shapes fuzzy 24-bin histogram. Assume again that the system classifies this blocks in the fourth bin which dictates the color. The combination of the three fuzzy systems are finally classify the block in 27-bin (1*24+3). The process is repeated for all the blocks of an image. At the end of the process, the histogram is normalized in the interval 0 to 1; each histogram value is quantized in three bits.

4. Implementation

The paper used image data set from the MPEG-7 Core Experiment (CE), which has 1000 images in the database. Most of the images in the database are natural images. Low level feature extraction techniques focus the color, texture and shape of an image in a database.

The following feature extraction techniques are used to extract the low level color feature in the database.

- CLD extraction technique which extracts the color and texture value of an image in a database.
- SCD extraction technique which extracts an image size in a database.
- EHD extraction technique which extracts an image shape in a database.
- Auto color correlogram extraction technique which extracts the spatial color value in a database.
- FCTH extraction technique which extracts the color and texture of an image in a database.
- CEDD extraction technique which extracts the color and edge of an image in a database.

The following algorithms are used for the low level color feature extraction technique in a database.

- DCT is suitable algorithm in color layout and edge histogram techniques for the color extraction.
- DWT algorithm is applied for color moment in FCTH technique.
- Fuzzy linking algorithm is applied for color expansion in FCTH and CEDD techniques.

5. Similarity Measure

Similarity measurement coefficient is used to measure the color distance between the images in FCTH and CEDD extraction CEDD techniques.

$$T_{ij} = t(X_i, X_j) = \frac{X_i^T X_j}{X_i^T X_i + X_j^T X_j - X_i^T X_j} \tag{1}$$

Where T_{ij} is the transformed value of point in an image *i* and j. X_i is the co-ordinate value of first point of an image. Y_j is the co-ordinate value of second point of an image. X_i^T is the transpose vector of X_i. Y_j^T is the transpose vector of Y_j. In the absolute congruence of the vectors, tanimoto coefficient takes the value 1; the QI is matched with the database image.

6. Experimental Results and Discussions

The low level feature extraction techniques proposed in this paper are tested on Corel database. The QI s 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 Average Image Retrieval Precision (IRP) and recall value as given in Equation 2 and 3 respectively.

$$IRP = \frac{Number \quad of \quad relevent \quad images \quad retrieved}{Total \quad number \quad of \quad images \quad retrieved} \tag{2}$$

$$Recall = \frac{Number \quad of \quad relevent \quad images \quad retrieved}{No. \quad of \quad relevent \quad images \quad in \quad the \quad database} \tag{3}$$

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. FCTH and auto color correlogram are good for texture images like butterfly, sunrise and flag images. CEDD and edge histogram are good for natural images like building, car and Tree images. FCTH, CEDD and edge histogram are good for color images like rose image. The present framework to evaluate CBIR based on recall and precision.

Table 1. Different types of query image category comparison.

Data Set	Color Layout		Scalable Color		Edge Histogram		Auto Color Correlogram		CEDD		FCTH	
Parameter	**IRP**	**Recall**	**IRP**	**Recall**	**IRP**	**Recall**	**IRP**	**Recall**	**IRP**	**Recall**	**IRP**	**Recall**
Butterfly	45	40	45	40	33	30	56	50	45	40	56	50
Sunrise	33	30	45	40	22	20	22	20	67	60	56	50
Rose	33	30	33	30	67	60	33	30	45	40	45	40
Car	56	60	45	40	45	40	33	30	67	60	33	30
Building	56	50	33	30	78	70	67	60	67	60	56	50
Flag	67	70	56	50	11	10	67	60	67	60	78	70
Tree	56	50	67	60	56	50	56	50	67	60	56	50
Average IRP Value	49	47	46	41	45	40	48	43	61	54	54	49

Table 1 shows that comparison of IRP and Recall value with different types of QI category as follows:

1. The average IRP value of color layout is 49%.
2. The average IRP value of scalable color is 46%.
3. The average IRP value of edge histogram is 45%.
4. The average IRP value of auto color correlogram is 48%.
5. The average IRP value of CEDD is 61%.
6. The average IRP value of FCTH is 54%.
7. The average recall value of color layout is 47%.
8. The average recall value of scalable color is 41%.
9. The average recall value of edge histogram is 40%.
10. The average recall value of auto color correlogram is 43%.
11. The average recall value of CEDD is 54%.
12. The average recall value of FCTH is 49%.

Table 2. Comparison of existing feature extraction technique with proposed system.

Data set	% Image Retrieval Precision Value for Existing System				% Image Retrieval Precision Value for Proposed System	
Query Image Category	**Local Neighboring Movement**	**Biased Discriminative Euclidean Embedding**	**Pyramidal Wavelet Decomposition**	**Local Tetra Patterns**	**CEDD**	**FCTH**
Butterfly	40	25	30	20	45	56
Rose	40	30	44	30	45	45
Car	40	30	40	10	67	33
Building	30	35	45	20	67	56
Tree	40	45	50	10	67	56
Average IRP Value	38	33	42	18	58	49

Table 2 shows that comparison of average precision value with the existing techniques.

1. Average precision value of local neighboring movement technique is 38%.
2. Average precision value of bias discriminative Euclidean embedding technique is 33%.
3. Average precision value of pyramidal wavelet decomposition technique is 42%.
4. Average precision value of local tetra patterns technique is 18%.
5. Average precision value of CEDD technique is 58%.
6. Average Precision value of FCTH Technique is 49%.

The Proposed techniques are compared with the existing Technique, CEDD and FCTH Image Retrieval Precision value has improved. Figure 3 shows that some sample images from the Database. Figure 4 shows that the Query Image. Figure 5 shows that the first 9 retrieved images from the database. Figure 6 shows that the % of Precision value for different types of QI Categories. Figure 7 shows that the comparisons chart for existing and proposed system.

Figure 3. Some sample images from the database.

Figure 4. Query image.

Figure 5. First 9 retrieved images from the database.

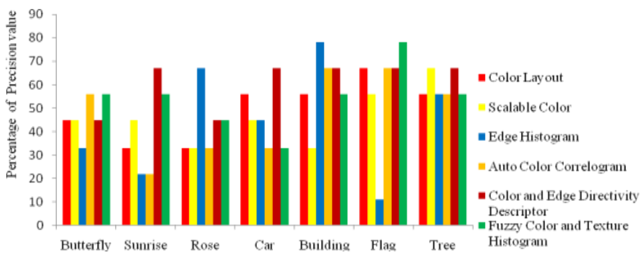

Figure 6. % of precision value for different types of query image categories.

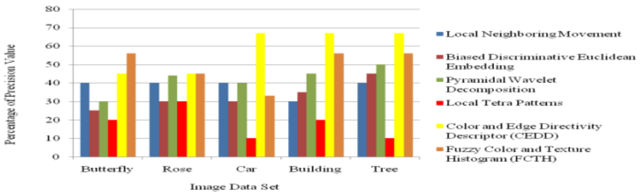

Figure 7. Comparison chart for existing and proposed system.

7. Conclusions and Future Works

From all the feature extraction techniques, it shows that the performance of FCTH and CEDD techniques are good in image retrieval. The Proposed technique is compared with the average precision value of the existing techniques, which gives the average precision value of CEDD technique is 58% and average precision value of FCTH technique is 49%. FCTH and CEDD are effective and efficient for image indexing and image retrieval. In future work the low level feature extraction techniques like Back Of visual Words (BOW) and Seeped Up Robust Feature (SURF) will improve the retrieval efficiency.

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