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Color and Edge Directive Descriptor Feature Extraction Technique for Content Based Image Retrieval System

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Abstract: The development of multimedia technology in Content Based Image Retrieval (CBIR) System is one of the prominent area to retrieve the images from a large collection of database. It is practically observed that any one algorithm is not efficient in extracting all different types of natural images. Hence a thorough analysis of certain color, texture and edge extraction techniques are carried out to identify an efficient 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 technique is proposed in this paper are tested on Corel database, which contains 10 categories of natural image dataset, each category has 100 images, totally the database has 1000 images. The feature vectors of the query image are compared with feature vectors of the database images to obtain matching images. This paper proposes Color and Edge Directivity Descriptor (CEDD) feature extraction technique which extract the matching image based on the similarity of color and edge of an image in the database. The Image Retrieval Precision (IRP) and Recall value of the proposed technique is 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 and Recall value. Also CEDD is effective and efficient for image indexing and image retrieval.

Key words: Content Based Image Retrieval (CBIR) · Image Retrieval Precision value (IRP) · Color and Edge Directivity Descriptor (CEDD)

INTRODUCTION

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, MPEG-7 Content descriptor, general image collection for licensing and natural collections. Content Based Image Retrieval (CBIR) shows an important role in data retrieval techniques. In CBIR system, the images are retrieved from large database based on the similarity in the characteristics of input query image rather than going into the details of description and tags, annotations of any particular image. It is set automatically extracting characteristic image are compared automatically and examine the role of query image, such as color, shape, texture, measures of similarity and finally get output best matching image and its relation to the information. 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, by comparing the feature of the query image. 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. 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

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between features of query image and every image in an image database. CBIR systems are based on many features such as texture, color and shape and edge information. Clustering algorithm has been widely used in computer vision, such as image segmentation and database administration. Clustering is to divide a set of objects that are allied vectors of multidimensional attributes into homogeneous groups such patterns within each job are equal. Clustering algorithms can be no broadly into two groups: partitioning and hierarchical. Partitioned clustering algorithm is mutually exclusive groups of spherical have emotional impact. Most partitioning clustering algorithm based distance. Tilt can be used to represent average cluster. Hierarchical clustering algorithm recursively nested groups locate either agglomeration mode or the split mode. 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 [6] or measurement in transform domain.

Related Work: The increase in electronic storage capacity and computing power have led to an exponential increase in the amount of digital content available to users in the form of images and videos, which form the basis of entertainment, educational and commercial applications. Consequently, search for the relevant information in the large space of the image and video databases have become more challenging. A typical image retrieval system has three major components (i) feature extraction (ii) High dimensional indexing (iii) system design. This paper discusses the first component that of feature extraction and selection. An image can be represented as a set of low level visual features such as color, texture and shape features. The process of determining the combination of features that is most representative of a particular query image is called the feature selection. 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) [11]. These two transforms are applied to different color models namely HSV and YCbCr separately in a given large standard database with 1000 images formed from 10 different classes taken from the Corel collection. The proposed features are very effective and efficient for image indexing and retrieval.

In many potential multimedia applications, Content Based Image Retrieval (CBIR) has gained more attention for web search and image management. In recent years to improve the performance of CBIR system, a wide variety of relevance feedback (RF) algorithms have been developed. These RF algorithms capture user preferences and bridge the semantic gap. This paper compares the conventional RF algorithms and shows a significant improvement in terms of accuracy and stability based on a subset of the Corel image gallery.

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 [12] 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) [13] 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. Empirical studies show that it is superior to the popular relevance feedback dimensionality reduction algorithms.

In-plane rotation and scale invariant features [14] 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. The view to achieve rotation and scale invariance in clustering, this method learns dictionaries and cluster images in the Radon transform domain.

Previous work content based image retrieval is utilized through calculating some of the primitive color features. The indexing of the image database is performed with SOM which identified the best matching units. Fuzzy color histogram [5] and subtractive fuzzy clustering algorithms have been utilized to identify the cluster for which the query image belonging. This approach only focus the primitive color features.

Clustering is more advantage to reduce the search time of the images in the database. In this grouping, each point has a degree of group membership and fuzzy logic, rather than also belong fully only one cluster.

Therefore, the points on the edge of a group can be in the group of lower grade than the points in the cluster center.

Clustering algorithms have been developed previously which includes fuzzy means. This class of algorithms is generalized to include the fuzzy co-variances [4,15]. 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 [2]. Experimental results are presented which indicate that more accurate clustering may be obtained by using fuzzy co-variances.

Co-ordinate logic filters [10], 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. To measure the extent of association between the images and the textual description of a concept, the likelihood of the occurrence of the images based on the characterizing stochastic process is computed. A high likelihood indicates a strong association. 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 [3].

The feature extraction techniques in the existing systems are (i) Color Layout Descriptor (CLD) Extraction (ii) Edge Histogram Descriptor (EHD) Extraction (iii) Auto Color Correlogram Extraction.

Color Layout Descriptor (CLD) Extraction: In CLD [9] Extraction process, the image consists of three color channels like R,G and B. The CLD descriptor was obtained through the following steps.

- The image can be loaded using file chooser and height and width of the image is obtained. So that the block width and block height of the CLD [1] are calculated by dividing by 8. The division is done by using truncation. If the image dimensions are not divisible by 8, the outermost pixels are not considered in the descriptor.
- By using the obtained information, the image data was divided into three 4D arrays for each color component. Pixels width in each block could also be accessed by providing the index of the block and index of the pixel inside the block.
- For each block a representative color was chosen by averaging the values of all the pixels. This results in three 8x8 arrays, one array contains each color component. In the first window, this step is directly visualized.
- Each of the 8x8 matrixes was transformed into the YCbCr color space.
- These YCbCr color space will be again transformed by 8x8 DCT (Discrete cosine Transform) [7] to obtain three 8x8 DCT matrices of coefficient.
- 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.

EDGE Histogram Descriptor (Ehd) Extraction: The EHD describes the distribution of non-edge cases as well as four directional edges and non-directional edges. The edge extraction scheme should be based on the image block as a basic unit for edge extraction rather than on the pixel. That is to extract directional edge features that need to define small square image blocks in each sub image. The paper divide the image space into non-overlapping square image blocks and extracts the edge information from them. In EHD Extraction, the image space divided into a fixed number of image blocks. The purpose of fixing the number of image blocks is to cope with the different resolutions of the images. The size of the block becomes variable and is proportional to the size of the whole image. In the image block, image size is assumed to be a multiple of 2. Thus pixels in the image are satisfied in that condition.

In this method to extract the edge feature of the image block is to apply 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.

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.
- The size of the feature is fairly small.

Informally a color correlogram of an image is table indexed by color pairs, where the entry specifies the probability of finding a pixel of color, at a distance from a pixel of color in the image. Such an image feature turns out to be robust in tolerating large changes in appearance of the same scene caused by changes in viewing positions, partial occlusions, changes in the background scene and camera zoom that causes radical changes in shape etc. The efficient algorithm is provided to compute the correlogram.

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.

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 3,4,5 Existing system. Section 6 is on overview of proposed approach and indexing, feature extraction. Section 7 Methodology and Section 8 experimental results. Finally, the conclusion is drawn in section 9.

Proposed Approach: The proposed approaches are explained as follows.

Color and Edge Directivity Descriptor (CEDD): 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.

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 Edge histogram descriptor 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.

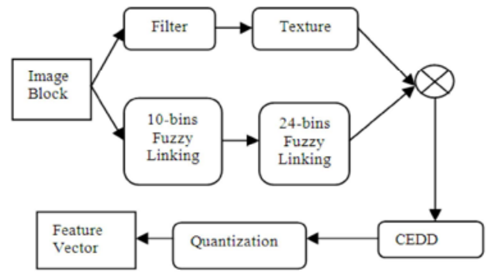

Fig. 1: Color and Edge Directivity Descriptor (CEDD) Extraction.

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 through the 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.

Methodology: 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.

- Color layout Descriptor (CLD) extraction technique which extracts the color and texture value of an image in a database.
- Edge Histogram Descriptor (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.
- Color and Edge Directivity Descriptor Extraction (CEDD) 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.

- Discrete Cosine Transform (DCT) is suitable algorithm in Color Layout and Edge Histogram Techniques for the color extraction.
- The Discrete Wavelet Transform (DWT) algorithm is applied for color moment in Fuzzy Color and Texture Histogram Technique.
- Fuzzy linking algorithm is applied for color expansion in Edge Directivity Descriptor Extraction (CEDD) Techniques.

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.

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

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

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.

Auto color Correlogram is good for Texture images like Butterfly, Sunrise and Flag images. CEDD and Edge Histogram are good for Natural images like Building, Car, Rose and tree images.

Table 1 shows that comparison of IRP and Recall value with Different types of Query Image Category as follows.

- The Average IRP value of Color Layout is 49%.
- The Average IRP value of Edge Histogram is 45%.
- The Average IRP value of Auto Color Correlogram is 48%.
- The Average IRP value of Color and Edge Directivity Descriptor is 61%.
- The Average Recall value of Color Layout is 47%.
- The Average Recall value of Edge Histogram is 40%.
- The Average Recall value of Auto Color Correlogram is 43%.
- The Average Recall value of Color and Edge Directivity Descriptor is 54%.

Table 1: Different types of Query Image Category comparison

Data Set	Color Layout		Edge Histogram		Auto Color Correlogram		Color and Edge Directivity Descriptor	
Parameter	IRP	Recall	IRP	Recall	IRP	Recall	IRP	Recall
Butterfly	45	40	33	30	56	50	45	40
Sunrise	33	30	22	20	22	20	67	60
Rose	33	30	67	60	33	30	45	40
Car	56	60	45	40	33	30	67	60
Building	56	50	78	70	67	60	67	60
Flag	67	70	11	10	67	60	67	60
Tree	56	50	56	50	56	50	67	60
Average IRP value	49	47	45	40	48	43	61	54

Fig. 2: Some Sample Images from the Database

Fig. 3: Query Image

Fig. 4: First 9 retrieved images from the database.

The average IRP value of CEDD is good compared to other techniques. The Proposed technique, Image Retrieval Precision value (IRP) has improved.

Table 2 shows that comparison of Average Precision value with the existing techniques.

- Average Precision value of Local Neighboring Movement Technique is 38%.
- Average Precision value of Bias discriminative Euclidean embedding Technique is 33%.
- Average Precision value of Pyramidal Wavelet Decomposition Technique is 42%.
- Average Precision value of Local tetra patterns Technique is 18%.
- Average Precision value of CEDD Technique is 58%.

The Proposed techniques are compared with the existing Technique, CEDD Image Retrieval Precision value has improved.

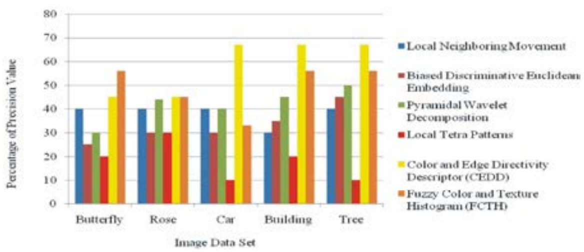

Fig. 5: % of Precision value for different types of Query Image Categories

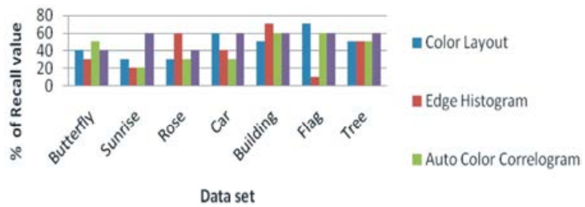

Fig. 6: % of Recall value for different types of Query Image Categories

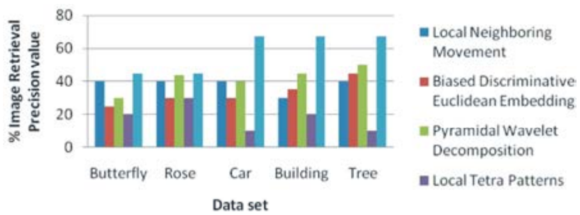

Fig. 7: Comparison chart for Existing and Proposed system

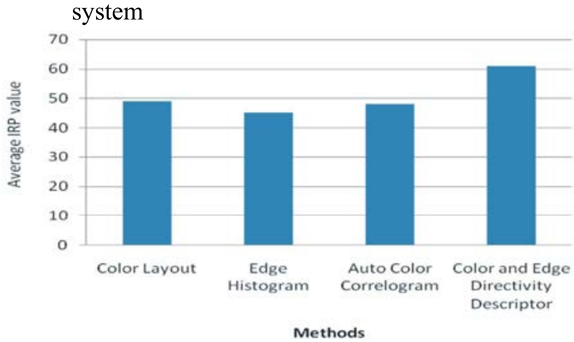

Fig. 8: Average IRP value for different types of Query Image Categories

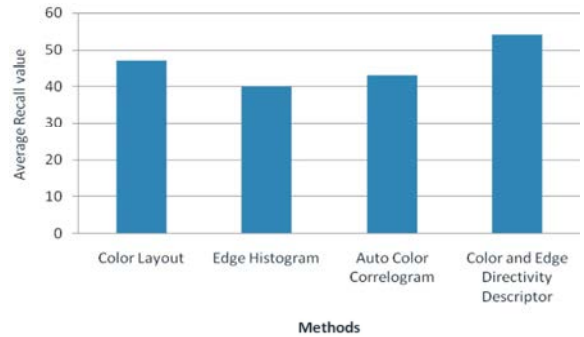

Fig. 9: Average Recall value for different types of Query Image Categories

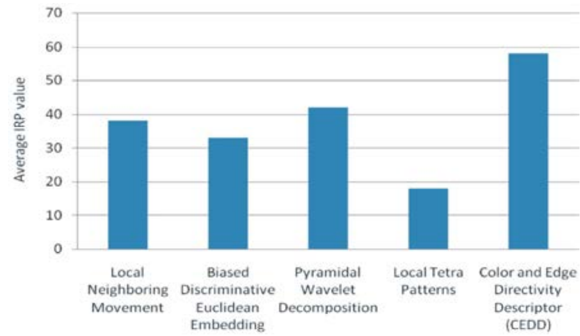

Fig. 10: Average IRP value Comparison chart for Existing and Proposed system

The present framework to evaluate CBIR based on recall and precision: Figure 8 shows that the average IRP value of different types of query images for various techniques. The CEDD has 61% which is good compared to other techniques. Figure 6 shows that the percentage Recall value for different types of Query Image Categories. Color Layout is good for flag image. Edge Histogram and Auto color Correlogram are good for Building image. CEDD is good for Sunrise, Car, Building, Flag and Tree images. Figure 9 shows that the average Recall value, CEDD has 54% which is good compared to other techniques. Figure 10 shows that the average IRP value for Existing and Proposed system. CEDD has 58% which is good compared to other techniques.

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	Color and Edge Directivity Descriptor (CEDD)
Butterfly	40	25	30	20	45
Rose	40	30	44	30	45
Car	40	30	40	10	67
Building	30	35	45	20	67
Tree	40	45	50	10	67
Average IRP value	38	33	42	18	58

CONCLUSION

From all the feature extraction techniques, it shows that the performance of CEDD techniques is very effective in image retrieval, which gives the good IRP and Recall value compared to the Existing Technique. In Different types of Query Image Category comparison, Average IRP value of CEDD technique is 61% and Recall value is 54%. The Proposed technique is compared with the Average Precision value of the existing techniques, which gives the Average Precision value is 58%. CEDD is effective and efficient technique for image indexing and image retrieval. In future work the low level feature extraction like Local Decagon Pattern based feature extraction Technique will improve the retrieval efficiency. This paper provides a detailed evaluation of the works carried out upon these techniques.

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