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Compact Descriptors For Accurate Image Indexing And Retrieval: Fcth And Cedd

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Abstract

Its FCTH and CEDD in this paper that deals with the extraction of a new low level feature that combines, in one histogram, color and texture information. This features are named FCTH - Fuzzy Color and Texture Histogram and CEDD - Color and Edge Directivity Descriptor. FCTH results from the combination of 3 fuzzy systems and size is limited to 72 bytes per image. CEDD size is limited to 54 bytes per image rendering these descriptors suitable for use in large image databases. CEDD is the low computational power needed for its extraction, in comparison with the needs of the most MPEG-7 descriptors.The proposed features are appropriate for accurately retrieving images even in distortion cases such as deformations, noise and smoothing. It is tested on a large number of images selected from proprietary image databases or randomly retrieved from popular search engines. To evaluate the performance of the proposed feature, the averaged normalized modified retrieval rank can be used (ANMRR).CEDD and FCTH are known as compact composite descriptors for content based image retrieval. Compact Composite Descriptors (CCD) are global image features capturing both, color and texture characteristics, at the same time in a very compact representation. In this paper implementing the proposed features in an image retrieval system to retrieve an image accurately based on the two descriptors FCTH and CEDD is done.

1. Introduction

The rapid growth of digital images through the widespread popularization of computers and the Internet makes the development of an efficient image retrieval technique imperative.Content based image retrieval, known as CBIR, 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. Most of the so far proposed retrieval techniques adopt methods in which more than one feature types are involved. For example, color and texture features are used in the QBIC [1], SIMPLICITY [2] and MIRROR [3] image retrieval systems.

The key to a successful retrieval system is to choose the right features that represent the images as accurately and uniquely as possible. The features chosen have to be discriminative and sufficient in describing the objects present in the image. To achieve these goals, CBIR systems use three basic types of features: color features, texture features and shape features. It is very difficult to achieve satisfactory retrieval results using only one of these feature types. To date, many proposed retrieval techniques adopt methods in which more than one feature type are involved. For instance, color, texture and shape features are used in both IBM's QBIC[4] and MIT's Photobook[5].

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.

In this paper a new set of descriptors is proposed and a method for their implementation in a retrieval system is described. The proposed descriptors have been designed with particular attention to their size and storage requirements, keeping them as small as possible without compromising their discriminating ability. The proposed descriptors incorporate color and texture information into one histogram while keeping their sizes between 23 and 74 bytes per image. The performance of the proposed descriptors is better than the performance of the similarly-sized MPEG-7 descriptors[6][7]. These descriptors appear to be in place to describe well enough the visual content of the image.

2. FCTH and CEDD Fuzzy Units

This paper proposes a new low level descriptor that includes in one quantized histogram color and texture information. This feature FCTH and CEDD 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 [8]. 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 re- lated to the hue of each color that is presented. First unit and second unit is same for both FCTH and CEDD.The third unit differs.

Next, in the third unit: For FCTH: each image block is trans- formed 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 and the process is described in 4.1 and 5.1.

With the use of the Gustafson Kessel [9] fuzzy classifier, 8 regions are shaped, which are then used in order to quantize the values of the 192 FCTH factors in the interval {0-7}, limiting thus the length of the descriptor in 576 bits per image. The process is described in section 6.1.For CEDD: 5 digital filters that were proposed in the MPEG-7 Edge Histogram Descriptor [10] are also used for exporting the information which is related to the texture of the image, classifying each image block in one or more of the 6 texture regions that has been fixed, shaping thus the 144 bins histogram. The process is described in section 4.2.Section 5.2 describes the entire proposed method implementation.With the use of the Gustafson Kessel fuzzy classifier 8 regions are shaped, which are then used in order to quantize the values of the 144 CEDD factors in the interval {0-7}, limiting thus the length of the descriptor in 432 bits. The process is described in section 6.2.

3. Color Segmentation for FCTH and CEDD

In [8], 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 [8].

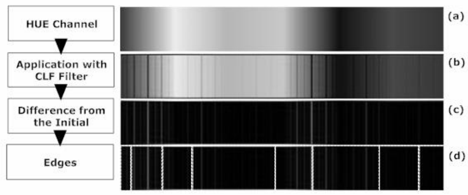

Figure 1: Edges extraction on H channel.

In this paper the work presented in [8] is further 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). Figure 1 shows the vertical edges of the channel H, which were used for determining the position of membership values .The selected hue regions are stressed by dotted lines in figure 1(d). The membership values limits of S and V are identified with the same process. The use of coordinate logic filters (CLF) [11] was 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.Based on these edges, the inputs of the system are analyzed as follows:

Hue channel is divided into 8 fuzzy areas. Their borders are shown in figure 2 and are defined as: (0) Red to Orange, (1) Orange, (2) Yellow, (3) Green, (4) Cyan, (5) Blue, (6) Magenta and (7) Blue to Red.

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 [12] 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.

For the evaluation of the consequent variables two methods have been used. Initially LOM (Largest of Maximum) algorithm was used. This method assigns the input to the output bin which is defined from the rule that gives the greater value of activation. Next a Multi Participate algorithm was tried. This method assigns the input to the output bins which are defined from all the rules that are being activated. Experimental results show that the second algorithm performs better. Next, a second system undertakes to separate each color in 3 hues. This system forms a 24 bins histogram as an output. Each bin represents a preset color as follows: (0) Black, (1) Grey, (2) White, (3) Dark Red, (4) Red, (5) Light Red, (6) Dark Orange, (7) Orange, (8) Light Orange, (9) Dark Yellow, (10) Yellow, (11) Light Yellow, (12) Dark Green, (13) Green, (14) Light Green, (15) Dark Cyan, (16) Cyan, (17) Light Cyan, (18) Dark Blue, (19) Blue, (20) Light Blue, (21) Dark Magenta, (22) Magenta, (23) Light Magenta.

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 filter (CLF) "AND" [11] was found to be appropriate for determining these vertical edges to

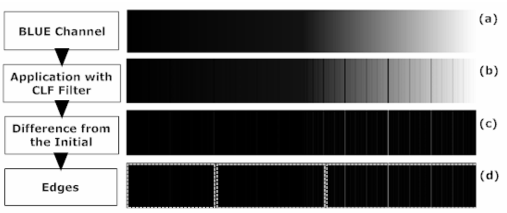

Figure 2: Vertical edge extraction by using CL filters.

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 analyzed as follows. Channel S as well as channel V are 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 labeled as follows: Dark Color(as Color is used the color that attributed by the first 10-Bins system) - Color and Light Color. A set of 4 TSK-like rules [12] with fuzzy antecedents and crisp consequents have been used. For the evaluation of the consequent variables, the Multi Participate method was also used.

4. Texture Segmentation

4.1 Fuzzy Texture Segmentation:

For exporting texture information from the images, three features that represent energy in high frequency bands of wavelet transforms were used. These ele- ments 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 de- scribed 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 $\{C_{kl}, C_{k,l+1}, C_{k+1,l}, C_{k+1,l+1}\}$. One feature is then computed as [2]:

$$f = \left(\frac{1}{4} \sum_{i=0}^{1} \sum_{j=0}^{1} C^2_{k+i,l+j} \right)^{\frac{1}{2}}$$

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. Mo- ments of wavelet coefficients in various frequency bands have proven effective for discerning texture. The intuition behind this is that coefficients in different fre- quency 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[2].

Elements f_{LH}, f_{HL} and f_{HH} are normalized and used as inputs in a fuzzy system, which shape a histogram of 8 bins (areas) as output.

These areas are analyzed as fol- lows: (0) Low Energy Linear area, (1) Low Energy Horizontal activation, (2) Low Energy Vertical activation, (3) Low Energy Horizontal and Vertical activation, (4) High Energy Linear area, (5) High Energy Horizontal activation, (6) High Energy Vertical activation, (7) High Energy Horizontal and Vertical activation. The inputs of the system are analyzed as follows: f_{HL} and f_{LH} are divided into 2 fuzzy areas and f_{HH} is divided into 2 fuzzy areas. A set of 8 TSK-like rules [12] with fuzzy antecedents and crisp consequents have also been used. For the evaluation of the consequent variables, the MultiParticipate method was also used.

4.2 CEDD Texture Information:

The 5 digital filters that were proposed by the MPEG-7 Edge Histogram Descriptor - EHD [10] [13], are shown in figure 3(A) . These filters are used for the extraction of the texture's information. They are able to characterize the edges being present in their application region as one of the following types: vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non-directional edges. The size of their application region will be described in section 5.2 and it is called henceforth *Image Block*.

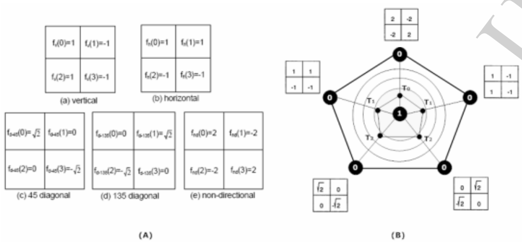

Figure 3. (A) Filter coefficients for edge detection , (B) Edge Type Diagram

Each *Image Block* is constituted by 4 Sub Blocks. The average gray level of each Sub-Block at (i,j)th Image-Block is defined as $a_0(i,j)$, $a_1(i,j)$, $a_2(i,j)$, and $a_3(i,j)$. The filter coefficients for vertical, horizontal, 45-degree diagonal, 135-degree diagonal, and non-directional edges are labeled as $f_v(k)$, $f_h(k)$, $f_{d-45}(k)$, $f_{d-135}(k)$, and $f_{nd}(k)$, respectively, where $k=0,\ldots,3$ represents the location of the Sub Block. The respective edge magnitudes $m_v(i,j)$, $m_h(i,j)$, $m_{d-45}(i,j)$, $m_{d-135}(i,j)$, and $m_{nd}(i,j)$ for the (i,j)th Image Block can be obtained as follows:

$$m_v(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_v(k)\right|$$

$$m_h(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_h(k)\right|$$

$$m_{d-45}(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_{d-45}(k)\right|$$

$$m_{d-135}(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_{d-135}(k)\right|$$

$$m_{nd}(i,j) = \left|\sum_{k=0}^{3} a_k(i,j) \times f_{nd}(k)\right|$$

Then the max is calculated:

$$\max = MAX(m_v, m_h, m_{d-45}, m_{d-135}, m_{nd})$$

and normalize all ***m.***

$$m_v' = \frac{m_v}{\max}, m_h' = \frac{m_h}{\max}, m_{d-45}' = \frac{m_{d-45}}{\max}, m_{d-135}' = \frac{m_{d-135}}{\max}, m_{nd}' = \frac{m_{nd}}{\max}$$

The output of the unit that exports texture's information from each Image Block is a 6 area histogram. Each area corresponds to a region as follows: EdgeHisto(0) Non Edge, EdgeHisto(1) Non Directional Edge, EdgeHisto(2) Horizontal Edge, Edge-Histo(3) Vertical Edge, EdgeHisto(4) 45-Degree Diagonal and EdgeHisto(5) 135-Degree Diagonal. The way that the system classifies the Image Block in an area is the following: Initially, the system checks if the *max* value is greater than a given thresh- old. This threshold defines when the Image Block can be classified as Texture Block or Non Texture Block (Linear). If the Image Block is classified as Texture Block, all the m' values are placed in the heuristic pentagon diagram of figure 3(B). Each m' value is placed in the line that determines the digital filter from which it was emanated. The diagram centre corresponds in value 1 while the utmost corresponds in value 0. If m' value is greater than the threshold in the line in which it participates, the Image Block is classified in the particular type of edge. Thus the Image Block can participate in more than one type of edge.

5.Implementation

5.1 FCTH Implementation:

The configuration of FCTH is resolved as follows: The histogram is constituted by 8 regions, as these are determined by the fuzzy system that takes decision with regards to the texture of the image. Each region is constituted by 24 individual regions, as these results from the second fuzzy system. Overall, the output that results includes 8 × 24 = 192 bins. Based on the content of the bins the respecting final histogram is produced.

In order to shape the histogram, we firstly dispatch the image in 1600 blocks. This number of blocks was chosen as a compromise between the image detail and the computational demand. Each block passes succes- sively from all the fuzzy systems. If we define the bin that results from the fuzzy system of texture detection as N and as M the bin that results from fuzzy system that shapes fuzzy 24-bins color linking histogram, then each block is placed in the bin position: N × 24 + M. Figure 4 illustrates the whole process, which is described next.

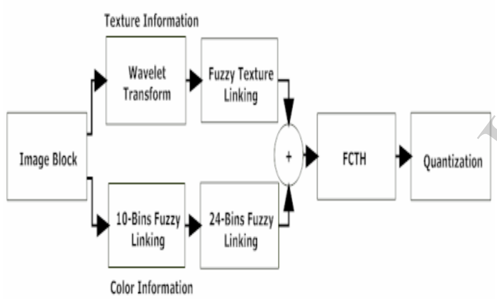

Figure 4: Combination of the three fuzzy systems.

Each block is transported in the YIQ color space and transformed with the Haar Wavelet transform. The fLH, fHL and fHH values are calculated and through the third fuzzy system this block is classified in one of its 8 out- put bins. Assume, for example, that the classification assigned this block to the second bin that defines low energy horizontal action. Next, the same block is trans- ported in the HSV color space and the mean H, S and V block values are calculated. These values constitute inputs in the fuzzy system that shapes the fuzzy 10- bins histogram described in section 3. Assume again, that the classification assigned this block to the fourth bin that defines that the color is red. Then, the second fuzzy system, using the mean values of S and V as well as the value of the bin (or bins) resulting from the 10- bins fuzzy linking system, calculates the hue of the color and shapes the fuzzy 24-bins histogram.

Assume again that the system classifies this block in the fourth bin which defines that color is the dark red. The combination of the 3 fuzzy systems finally will classify the block in the 27th bin(1*24+3).The process is repeated for all the blocks of the image. At the completion of the process, the histogram is normalized in the interval {0-1} and quantized in 3 bits/bin. The quantization process is described in the following section 6.1.

5.2 CEDD –Implementation

The configuration of CEDD is resolved as follows:
The unit associated with the extraction of color information is called Color Unit. Similarly, the Texture Unit is the unit associated with the extraction of texture information. The CEDD histogram is constituted by 6 regions, determined by the Texture Unit. Each region is constituted by 24 individual regions, emanating from the Color

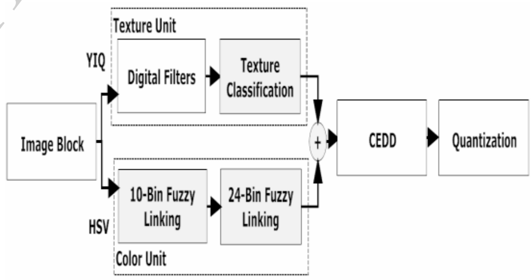

Figure. 5 CEDD flowchart

Unit. Overall, the final histogram includes 6 × 24 = 144 regions. In order to shape the histogram, firstly we separate the image in 1600 Image Blocks. This number was chosen in order to compromise between the image detail and the computational power. Each Image Block feeds successively all the units. If we define the bin that results from the Texture Unit as N and as M the bin that results from the Color Unit, then the Image Block is placed in the output histogram position: N × 24 + M. In the Texture Unit, the Image Block is separated into 4 regions, the 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. Each Image Block is then filtered with the 5

digital filters that were described in section 4.2, and with the use of the pentagon's diagram it is classified in one or more texture categories. Assume that the classification resulted in the second bin, which defines NDE (Non Directional Edge).
In the Color Unit, every Image Block 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 that the color is red. Then, the second fuzzy system (24- Bin Fuzzy Linking), using the mean values of S and V as well as the value of the bin (or bins) expense from the previous system, calculates the hue of the color and shapes the fuzzy 24-bins histogram. Assume again that the system classifies this block in the fourth bin which dictates that color is the dark red. The combination of the 3 fuzzy systems finally will classify the block in the 27 bin (1 × 24 + 3). The process is repeated for all the blocks of the image. At the completion of the process, the histogram is normalized in the interval {0-1}. Each histogram value is then quantized in 3 bits. The quantization process is described in section 6.2.

6.Quantization

6.1 FCTH- Quantization

For the restriction of the FCTH length, a 3bits/bin quantization was used, limiting thus its total length in 192 × 3=576 bits. To calculate the quantization table,assume a sample of 10000 images was used. Initially, FCTH vectors were calculated for the total of images. The crowd of 10000 ×192 elements constitutes the entry of the fuzzy Gustafson Kessel classifier [9], which separates the crowd of samples in 8 regions. Basically this classification maps the bin values from the decimal area {0-1} to the integer area {0-7}.
Gustafson Kessel parameters were selected to be: Clusters: 8, Repetitions: 2000, e=0.002, m=2. The resulting quantization is given in table 1. The entries of the table have the following meaning. The values of the histogram appearing in bins 0-47 are assigned to one of the values {0-7} according to the minimum distance of each bin value from one of the eight entries in the first row of the table. The same procedure is followed for the entries of bins 48-143 and 144-191 where in this case the eight entries of the second and the third row respectively are used.

Table 1: Normalization table (Multiplication by 10^7)

Bin: 0-47	Bin:48-143	Bin:144-191
13	23	18
931	1732	2373
2243	3911	4145
4312	6933	5391
8316	7912	6912
10143	9098	8198
17484	16179	9179
22448	18472	12472

6.2 CEDD- Quantization

For the restriction of the CEDD length, a 3bits/bin quantization was used, limiting thus its total length in 144 × 3=432 bits.Assume a sample of 10000 images was used to calculate the quantization table. Initially, CEDD vectors were calculated for the total of images. The crowd of 10000 × 144 elements constitutes the entry of the fuzzy Gustafson Kessel classifier [9], which separates the volume of the samples in 8 regions. Basically this classification maps the bin values from the decimal area {0-1} to the integer area {0-7}.

Table 2. Quantization Table

Bin: 0-23	Bin:24-47	Bin:48-95	Bin:96-143
0.00018	0.00020	0.00040	0.00096
0.02373	0.02249	0.00487	0.01075
0.06145	0.06025	0.01088	0.02416
0.11391	0.12070	0.01816	0.04155
0.17912	0.18112	0.02704	0.06289
0.26098	0.23413	0.03812	0.09306
0.34179	0.32566	0.05267	0.13697
0.55472	0.52070	0.07955	0.26289

Gustafson Kessel parameters were selected to be: Clusters: 8, Repetitions: 2000, e=0.002, m=2. The resulting quantization is given in Table 2. The entries of the table have the following meaning: The values of the histogram appearing in bins 0-23 are assigned to one of the values {0-7} according to the minimum distance of each bin value from one of the eight entries in the first row of the table. The same procedure is followed for the entries of bins 24-47, 48-95 and 96-143 where in this case the eight entries of the second, the third and the fourth row respectively are used.

7. Similarity measure

For the measurement of the distance of FCTH feature between the images we choose to use Tanimoto coefficient [14].

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

Where 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

ANMR(Averaged Normalized Modified Retrieval Rank)[7] :

It is used in order to evaluate the performance of the image retrieval system. The average rank *AVR (q)* for query *q* is:

$$AVR(q) = \sum_{k=1}^{NG(q)} \frac{Rank(k)}{NG(q)}$$

Where

- *NG (q)* is the number of ground truth images for query *q*. As ground truth we define a set of visually similar images.
  - *K = min (2 × NG (q), 2 × GMT)*

  where GTM = max {NG (q)}.
- Consider a query . Assume that as a result of the retrieval, the k^{th} ground truth image for this query *q* is found at a position *R*. If this image is in the first *K* retrievals then *Rank (k)=R* else *Rank (k) = (K+1).*

•*Rank (k)* is the retrieval rank of the ground truth image.

The modified retrieval rank is:

$$MRR(q) = AVR(q) + 0.5 - 0.5 * NG(q)$$

Note that *MRR* is 0 in case of perfect retrieval. The normalized modified retrieval rank is computed as

$$NMRR(q) = \frac{MRR(q)}{K + 0.5 - 0.5 * NG(q)}$$

Finally average of *NMRR* over all queries defined as:

$$ANMRR(q) = \frac{1}{Q}\sum_{q=1}^{Q} NMRR(q)$$

The ANMRR is always in range of 0 to 1 and the smaller the value of this measure is, the better the matching quality of the query is. ANMRR is the evaluation criterion used in all of the MPEG-7 color core experiments. Evidence was shown that the ANMRR measure approximately coincides linearly, with the results of subjective evaluation about retrieval accuracy of search engines. A set of ground truth images that are most relevant to query were identified.

8.Experimental results

Our test data consists of several images belonging to different categories.FCTH and CEDD was used in the retrieval procedure.Some of the retrieved images for sample test images are shown below . A set of ground truth images that are most relevant to query were identified. The ground truth data is a set of visually similar images

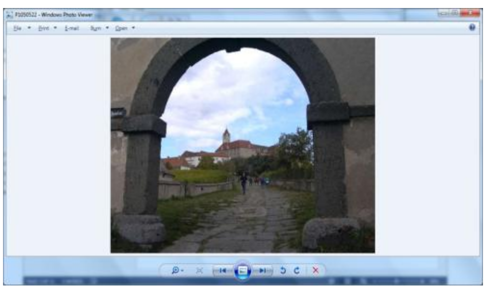

Figure 6:Query Image

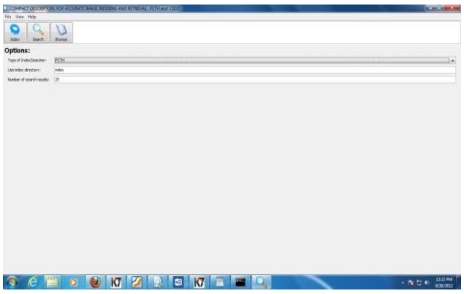

Figure 7:Type of searcher:FCTH

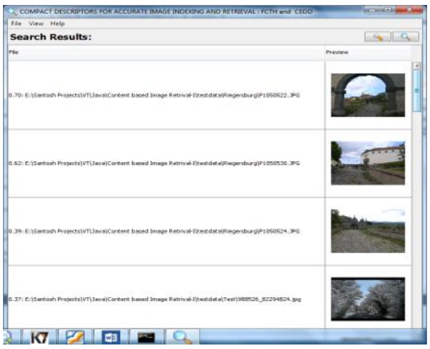

Figure 8 Output for query image (FCTH)

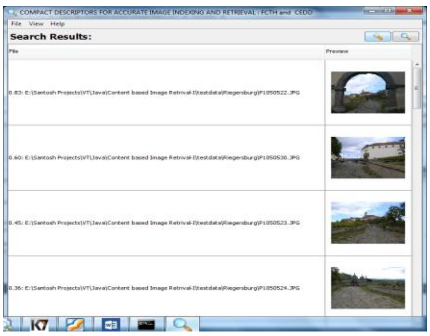

Figure 9 Output for query image (CEDD)

To evaluate the performance of the image retrieval system, the objective measure called ANMRR (Aver- aged Normalized Modified Retrieval Rank) is used. The ANMRR is always in range of 0 to 1 and the smaller the value of this measure is the better the matching quality of the query. ANMRR is the evaluation criterion used in all of the MPEG-7 color core experiments.ANMRR w.r.t different search engines like WANG'S database proved FCTH and CEDD with smaller measure(ANMRR)values which proves better matching quality of query.

Color Descriptors: Dominant Color Descriptor (DCD), Scalable Color Descriptor (SCD), Color Layout Descriptor (CLD), Color Structure Descriptor (CSD). Texture Descriptors: Edge Histogram Descriptor (EHD), Homogeneous Texture Descriptor (HTD).

Table 3.ANMRR Results for descriptors(Wang's Database)

DCD	0.45
SCD	0.36
CLD	0.40
CSD	0.32
EHD	0.51
HTD	0.71
FCTH	**0.27**

Table 4.ANMRR Results for descriptors(Wang's Database)

DCD	0.4959
SCD	0.3566
CLD	0.3999
CSD	0.3162
EHD	0.5088
HTD	0.7054
CEDD	**0.2431**

9.Conclusion

This paper presents the extraction of a new low level feature that contains, in one histogram, color and texture information. This element is intended for use in image retrieval and image indexing systems.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. The descriptor for search is chosen based on the query image. The most appropriate descriptor is chosen at similarity assessment time, so within a single query the chosen descriptor may be different for different image pairs. Given that the color information in all two descriptors is the same, the factor that will determine the suitability and capability of each descriptor is mainly found in the texture information.

Based on the fact that the color information given by the 2 descriptors comes from the same fuzzy system, we can assume that joining the descriptors will result in the combining of texture areas carried by each descriptor leading to a joint composite descriptor for future study.

10.References

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