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AN APPROACH TO CONTENT BASED IMAGE RETRIEVAL SYSTEM

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***Abstract*— An intuitive approach for Content Based Image Retrieval using Block Truncation coding techniques is presented. In the encoding(feature extraction) stages the bitmap along with [1]Quantization vectors ,namely Color Co-occurrence Feature (CCF) and [2]Bit Pattern Features (BPF) are used for indexing and to generate the visual codebook. These two features can be directly extracted from the sample image, and while comparing decompression can be utilized in the image retrieval. The proposed system performs the functions of the existing system such as image compression and storage but also generate a simple descriptor for indexing the image in CBIR systems . The Quadratic Distance method, though yields metric distance, is computationally expensive. The conventional Integrated Region Matching is non-metric and hence gives results that are not optimal. Our system uses a modified IRM method which overcomes the disadvantages of both the above mentioned methods. The color feature is extracted using the commonly adopted histogram technique.An interface is provided to the user to enter the image as input. . The colour feature is automatically extracted from the query image and is compared to the images in the database retrieving the matching images.**

Keywords—Digital Image Processing,Bit patternfeature, Color co occurance features, Integrated Region matching

I. INTRODUCTION

During the initial stages of the computer history most of the data that was stored was either text or some numerical data that was easily structured, efficiently searched and indexed so that it could later be searched and indexed an accessed in an efficient manner. But as the technology improved, it became possible to store various types of data that were in no way structured or related. Thus new and intuitive techniques were needed to effectively store and retrieve this data in an efficient manner.

One approach to tackle this problem in case of images was the use of tags to describe the image. These tags were textual description of the most prominent features visible in the corresponding image. But this type of storage and indexing in highly subjective to the users who tag the image. Also this type of storage take takes lot of space and takes a lot of processor time to compute the needed results.

Alternate implementation for image retrieval was done using digital image processing. This approach was called Content Based Image Retrieval. [1]Several Techniques were developed to implement this functionality.

Some previous work keeps an eye on investigating which visual features are important for those images. Based on the intermediate queries some relevant images (positive examples) picked up by the users at the end of each feedback (also called iteration in this paper). Solution for enhancing the accuracy of image retrieval is moving the query description towards the boundary of the user's preference in visual feature space. QPM [3]considers multiple positive examples of images as a new query point at each feedback. After several noticeable changes of descriptors for location and contour, the query point should be close to a convex region of the user's interest.

The problem involves submitting an image as a query into the proposed software application that is designed to use CBIR techniques in extracting the visual descriptor properties, and matching them.

One of the challenges faced in pattern recognition is accurate perception of the object in uncontrolled lighting conditions. This could be addressed by using the combination of various techniques like illumination normalization, local texture, distance transform based matching and multiple feature fusion.

In another approach local region of the image represented by local maximum edge binary patterns, which can be determined by taking the absolute difference between the center pixel and its immediate neighbors. In this approach the information of the image is extracted from the edges present in the image itself. The effectiveness of this algorithm can be improved by the use of Gabor transform.

In another approach[2] for pattern recognition use of high level order local derivative pattern employs the use of framework to encode directional features based on local derivative variations. The LDB templates extract local information through spatial relationship in a given local region. Grey level images and Gabor feature images are used to evaluate differences in local derivative pattern and local binary pattern.

Local tetra patterns (LTP) [4]can be used to index images, which can then be employed for content based image retrieval. By computing the grey level difference the relationship between local binary pattern and local ternary pattern is established. Using the first order derivatives in vertical and horizontal directions we establish a relation between a pixel and its neighbors. This can be generalized and we compute the nth order LTP using nth order derivatives in vertical and horizontal directions which can be used to analyze the effectiveness of the current algorithm along with Gabor transform.

Modified color motif co-occurrence matrix (MCMCM)[5] can be used to obtain the inter correlation between the RGB color planes which are not present in Color motif co occurrence matrix. The difference between MCMCM and pixels of the scan pattern are integrated with equal weights. This is contrasted with a system similar[2] to one along with color histogram that utilizes k means algorithm with optimized weights.

II. PROPOSED SYSTEM

The major difference between the proposed approach and other contemporary approaches is that an approximation to an optimal solution is done to resolve the problems existing in current RF, such as redundant browsing and exploration convergence. In order to resolve this, the approximated solution takes advantage of the feature descriptors, that is, exploited knowledge (navigation patterns) to assist the proposed system in formulating a search strategy for efficiently hunting the desired images from a collection of vast image set. Generally, the task of the proposed system can be divided in the form of two major operations, namely offline knowledge discovery and online image retrieval.

The objective goal of Content-Based Image Retrieval (CBIR) systems is to operate on a database of collections of images and, in based on the visual queries, extract all relevant images ordering them on the basis of relevance based on a ranking algorithm. The application potential of CBIR for fast and efficient image retrieval is enormous.

A. Local color histograms

Local Color Histograms divides the images[1] into fixed blocks and for each block obtain its histogram. This approach includes information regarding the distribution of colors of various intensities present within the regions. The first step is to divide the image into tiny little blocks and then obtain a local color histogram for each of these tiny blocks. The original image will then be represented by using these obtained local histograms. When comparing the current image with another set of images, we calculate the distance, using the values obtained through their histograms, between a region in one image and the exact same region at the same location in the corresponding image for the purpose of correction. The distance between the two images will be determined by the aggregation of all these distances.

In the graphical description the horizontal x-axis represents the range of brightness from 0 (darkness) on the left to 255 (brightness) on the right. It can be visualized as a line with 256 empty slots on which to place pixels of the same brightness one after another. Since these are the only values that can be captured by the image obtained from a camera, the horizontal line also describes the camera's maximum potential dynamic range.

The vertical y-axis represents the number of similar pixels that have, each one, made of the 256 brightness (intensity) values. The higher the distance of the line coming from the horizontal axis, the greater is the number of pixels there are at that level of brightness.

To analyze the histogram, the distribution of pixels represented by the curve is viewed. An image that utilizes the entire dynamic range of the digital camera, ranging from the brightest spots to the darkest regions will have a nearly homogenous distribution in number of pixels at every level of brightness, allowing proper analysis and avoiding overlooking of certain rare pixel varieties. An image having low contrast will tend to have the pixels clumped together and have a narrower dynamic range.

B. HISTOGRAM QUADRATIC DISTANCE MEASURES

In order to address the drawbacks of Minkowski-form metrics[4] wherein comparisons takes place among "like" bins, quadratic-form metrics also takes into consideration the cross-relation of the bins. As represented in the following equation. The quadratic-form metrics compare all bins and determines weight due to the inter-element distance that is obtained by the determination of weighting factors for each pair of blocks.

The IBM QBIC system developed a quadratic-form metric for color histogram-based image retrieval, that reports the quadratic-form metric between color histograms providing a much greater degree of desirable results when compared to like color only comparisons. The quadratic-form distance between color histograms hq and ht (is given by:

$$\mathcal{D}4(\mathrm{q},\mathrm{t}) = D4^2 = (\mathbf{h}_\mathrm{q} - \mathbf{h}_\mathrm{t})^T \mathbf{A} (\mathbf{h}_\mathrm{q} - \mathbf{h}_\mathrm{t}),$$

Quadratic-form metrics compare multiple bins between the color histogram using a similarity matrix A = [aij], which can take into account color similarity or color Covariance.

C. INTEGRATED REGION MATCHING

IRM incorporates the properties of all segmented regions so that the information about an image present scattered in individual regions can be utilised completely. Region-Based matching is a demanding problem because of inaccurate segmentation due to lcal maxima minima that frequently arise. Semantically precisean d accurate image segmentation is extremely difficult to implement and is still an open problem in computer visionthe is not yet solved to requirements. For example, a typical segmentation algorithm can segment a sun into two regions: the object, namely sun and the background of the object. The same algorithm may segment another image of a sun into several regions: the chroma of the sun, the bright region around the sun, the sky, the clouds, the background forest and the ground.

The distance irm(X, Y) between two images X and Y is algorithmically described and works as follows. Initially the default distances dhist (Xi, Yj) between the pairs of levels are computed, checked for the monge condition, and ordered. Additionally, all levels are initialized as default non-matched with a value equal to 0. The resultant distance dhist (Xi, Yj) depends on the visual features extracted from the levels. In our case it is weighted composition of the distance between the histogram levels and the distance between the sizes of the levels (bins).

After ordering the distances, the first value corresponds to the best possible match between a level of image X and a level of image Y. The second value displayed corresponds to the second best match and the third to the third best match and proceeds to produces matches until otherwise specified. For each distance denoted by dhist(Xi, Yj), a specific set is used for representation in a non-decreasing order, if both levels are marked as non-matched, and check the monge condition, the size of levels Xi and Xj are compared. The size of the smallest level determines the weight w that multiplies the values dhist (Xi, Yj) in order to obtain the final distance between the images (β). This weight represents to percentage of matching between the two images with that distance.

Hoffman demonstrated that, if distance matrix satisfies the monge condition, then greedy approach gives optimal solution.

$$a_{ij} + a_{kl} \leqslant a_{il} + a_{kj} \quad \text{for any } i < k,\ \ j < l$$

Our histogram distance matrix function implicitly satisfies the monge condition. Hence our approach gives optimal solution that is metric distance unaffected by other values. So we called our modified IRM, True IRM.

Pseudocode:

```
IRM(X,Y)
          FOR EACH PAIR OF HISTOGRAM LEVELS
Xi Є X and  Yi Є Y
              Xi.status = Yj.status = 0
              Compute Dhist(Xi,Yj) and check the monge
condition
          β = 0
              counter=2n-1
          FOR  EACH  Dhist  (Xi,Yj)  IN  A  NON-
DECREASING ORDER
              if Xi.status = Yj.status = 0
                  if Xi.size < Yj.size
                      w=Xi.size
                      Yj.size = Yj.size-Xi.size
                      Xi.status = 1
                  ELSE
                      w=Yj.size
                      Xi.size= Xi.size – Yj.size
                      Yj.status = 1
                      if Xi.size = 0 then Xi.status = 1
    β = β + w* Dhist(Xi,Yj)
counter=counter-1
                        if (counter==0) then
        return β;
```

III. SYSTEM DESIGN

. 1. COLOR HISTOGRAM MODULES :

In this paper,we defines the color histograms obtained as a result of previous functions using bins[1]. Each of these bins represent the probability of color that is represented using the bin. A local colour histogram H for a given image is defined represented by the vector:

H={ H[0], H[1], H[2],……..H[I],……H[N] }

Here I represents a color in the color histogram and it corresponds to a sub cube in the Red-Green-Blue color space, H[I] is the number of pixels in a particular color present in that image, and N is the number of bins representing colors in the color histogram, that is, the number of colors the proposed system of color module.

(i)RGB color model

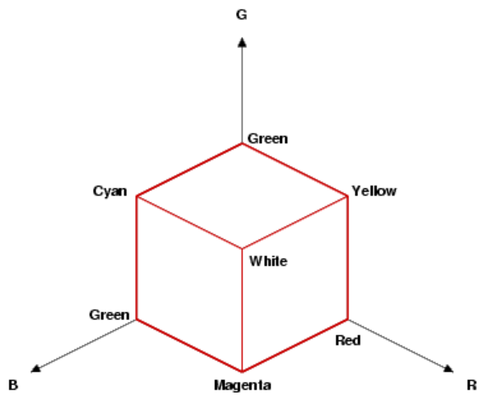

FIG 1. RGB coordinates system

The RGB color model is composed of the primary pallet colours namely Red, Green, and Blue. This system defines the color model that is used in the age old CRT monitors and displays that use color raster graphics. These colors are considered the primary colors, since these colours, when added in varying proportions ,produce the desired color. The proposed RGB model can be described using the Cartesian coordinate system as shown in the above figure. The diagonal from the origin point (0, 0, 0) representing black to (1, 1, 1) representing white, which shows the grey-scale format of the display.

(ii)THE GLOBAL COLOR HISTOGRAM

As we have discussed, the color histogram depicts color distribution of various colors using a set of bins. Using the Global Color Histogram (GCH), [5]an image can be encoded with its color histogram describing the overall color distribution, and the distance between two images, under consideration will be determined by the aggregation of the distances between their color histograms. The following diagrams shows how a GCH looks for distinct primary colors

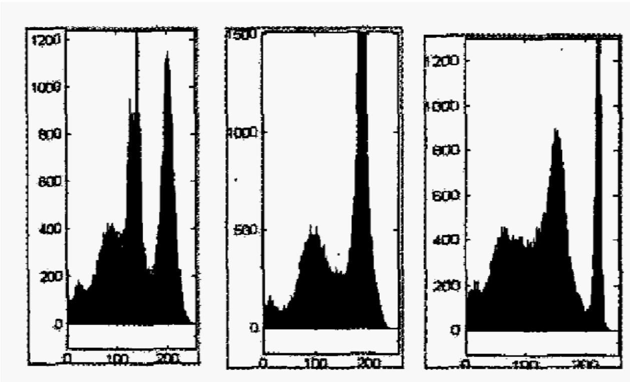

FIG2: GLOBAL COLOR HISTOGRAM

The Global Color Histogram is a conventional method for color-based image retrieval. The main drawback is that it does not include information regarding the color distribution of the various regions, so the perceived distance between images sometimes does not show the actual difference between images. For example, the displayed distance between images A and C should not be larger than the actual distance between images A and B, but using the Global Color Histogram we obtain the same distance even if they are different in smaller regions. Also, in the case of using a GCH, it is widely possible for two distinct images to have a very short distance between their global color histograms, such as in the above example, resulting which, the images B and image C are treated as the same. This is one of the main limitation of GCHs.

(iii)LOCAL COLOR HISTORAM

This approach also referred to as LCH, includes all information regarding the color distribution of various regions. The first step is to segment the image into smaller more manageable blocks and then to obtain a color histogram, called local color histogram, for each block. The image will then be collectively, represented by these histograms[3]. During the comparison of the two images, we calculate the total distance, using their local color histograms, between a region in one image and a corresponding region in same location in the other image which is being considered for matching. The total distance between the two images will be determined by the aggregation of all these distances. By using the square root of Euclidean distance as the metric distance between color histograms, the distance metric between two measurable images is chosen and used in the LCH. This is defined as:

$$d_{LCH}(Q,I) = \sum_{k=1}^{M} \sqrt{\sum_{i=1}^{N} (H_Q^k[i] - H_I^k[i])^2}$$

TEXTURE MODULES:

(i)Co-occurrence matrices

•based on repeated occurrence of a particular color configuration representing a particular grouping in the texture

•this configuration differs more in finer textures, while the varying gradient is slower for coarser textures

•occurrence of the distinct gray-level configuration can be succinctly described by the matrices representing frequencies of relative magnitudes, called co-occurrence matrices

$$\begin{aligned}
P_{0^\circ,d}(a,b) &= |\{((k,l),(m,n)) \in D : \\
&\quad k-m=0, |l-n|=d, \;\; f(k,l)=a, f(m,n)=b\}| \\
P_{45^\circ,d}(a,b) &= |\{((k,l),(m,n)) \in D : \\
&\quad (k-m=d, l-n=-d) \;\; OR \;\; (k-m=-d, l-n=d), \\
&\quad f(k,l)=a, f(m,n)=b\}| \\
P_{90^\circ,d}(a,b) &= |\{((k,l),(m,n)) \in D : \\
&\quad |k-m|=d, l-n=0, \;\; f(k,l)=a, f(m,n)=b\}| \\
P_{135^\circ,d}(a,b) &= |\{((k,l),(m,n)) \in D : \\
&\quad (k-m=d, l-n=d) \;\; OR \;\; (k-m=-d, l-n=-d), \\
&\quad f(k,l)=a, f(m,n)=b\}|
\end{aligned}$$

•these matrices are usually symmetric but asymmetric definition in case of unique images is also possible

(ii)EDGE Frequency:

•These are features based on distance-related variations

•micro-edges are to be detected using operators for manipulating small distances

•macro-edges can be detected easily by the use of large-size edge detectors

•g(d) is a texture description function that is distance-dependent:

$$\begin{aligned}
g(d) = \;& |f(i,j) - f(i+d,j)| + |f(i,j) - f(i-d,j)| + \\
& |f(i,j) - f(i,j+d)| + |f(i,j) - f(i,j-d)|
\end{aligned}$$

•g(d) is similar to autocorrelation function for negative values

•dimensionality of texture description is determined by the number of considered distances’ d’ while calculating.

3. Intermediate Result Processing:

A query to a content based image retrieval system varies, In a large scale image database present on a device, is considerably different from processing it from a PC where the user has considerably more interaction with the system namely PC and software ,and is involved in the ongoing query operation. A naïve End-User has no idea how the query process is progressing at the server side nor does he know how long it will take to complete the query operation. Finally, wireless network delay, in addition to the long query time, is noticeably frustrating for the user. Therefore, the system must be responsive to the user, giving him a rough idea as the progress of the search.

IV. CONCLUSION

In this paper, a novel approach to content based image retrieval system is presented that exploits the encoded data stream pattern to construct the image features, namely Color Co-occurrence descriptors and Bit Pattern features extracted for each image block. The proposed scheme can provide the better average accuracy compared to various former techniques in practice. As a result, the proposed system can be considered as an attractive alternative to the several color image retrieval applications.

For the further studies, the proposed image retrieval system can be modified and improved can be effectively applied to video retrieval. The video can be viewed as sequence of related images in which the proposed indexing can be applied directly in this image sequence. The indexing scheme for the current RGB scheme can also be extended to another color space, such as YCbCr. Additional features can be added by extraction from the data stream excluding CCF and BPF that can be used to enhance the retrieval performance. In the future the system could be programmed to be made able bridge the gap between explicitly specified knowledge semantic, image content descriptors, and also the subjective criteria like mood and feel, in a framework for human-oriented testing, assessment and evaluation.

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