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Content Based Image Retrieval Based on YCbCr Approach

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ABSTRACT: Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. This approach uses Histogram attributed relational graphs (HARGs) to represent images , where each node in the graph represents an image region and each edge represents a relation between two regions . The given query is converted to a FARG, and a low complexity Histogram graph matching algorithm is used to compare the query graph with the FARGs in the database.

KEYWORDS: YCbCr Approach, Image Detection, Image Retrieval, Content Based Image Retrieval, CBIR etc.

I. INTRODUCTION

"Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because most web based image search engines rely purely on metadata and this produces a lot of garbage in the results. Also having humans manually enter keywords for images in a large database can be inefficient, expensive and may not capture every keyword that describes the image. Thus a system that can filter images based on their content would provide better indexing and return more accurate results.

Content-based image retrieval, a technique which uses visual contents to search images from large scale image databases according to users' interests, has been an active and fast advancing research area since the 1990s. During the past decade, remarkable progress has been made in both theoretical research and system development. However, there remain many challenging research problems that continue to attract researchers from multiple disciplines.

One of the tools that will be essential for future electronic publishing is a powerful image retrieval system. The author should be able to search an image database for images that convey the desired information or mood; the reader should be able to search a corpus of published work for images that are relevant to his or her needs. Most commercial image retrieval systems associate keywords or text with each image in the corpus and require the user to enter a keyword or textual description of the desired image. Standard text retrieval techniques are then used to identify the relevant images. Unfortunately this text-based approach to image retrieval has numerous drawbacks. Associating keywords or text with each image is a tedious and time-consuming task since it must be done manually or at best semi-automatically; image processing technology is not advanced enough to allow the automatic construction of textual image descriptions except in well-defined and tightly focused domains. Some image features may not be mentioned in the textual description due to design decision or indexer error; these image features do not exist from the standpoint of the retrieval system and any query that mentions them will fail. Some features are \nearly impossible to describe with text"; for example many textures and shapes defy easy description. Finally different indexers { or even the same indexer { may describe the same feature with different terms or different features with the same term; these are the standard text retrieval problems of synonymy and polysemy.

Content-based image retrieval, uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. In typical content-based image retrieval systems (Figure 1-1), the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with example images or sketched figures. The system then changes these examples into its internal representation of feature vectors.

The similarities /distances between the feature vectors of the query example or sketch and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image database. Recent retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaningful retrieval results.

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A visual content descriptor can be either global or local. A global descriptor uses the visual features of the whole image, whereas a local descriptor uses the visual features of regions or objects to describe the image content. To obtain the local visual descriptors, an image is often divided into parts first. The simplest way of dividing an image is to use a partition, which cuts the image into tiles of equal size and shape. A simple partition does not generate perceptually meaningful regions but is a way of representing the global features of the image at a finer resolution. A better method is to divide the image into homogenous regions according to some criterion using region segmentation algorithms that have been extensively investigated in computer vision. A more complex way of dividing an image, is to undertake a complete object segmentation to obtain semantically meaningful objects (like ball, car, horse). Currently, automatic object segmentation for broad domains of general images is unlikely to succeed.

II. RELATED WORK

Sangoh Jeong, "Histogram-Based Color Image Retrieval", showed that images retrieved by using the global color histogram may not be semantically related even though they share similar color distribution in some results. An image retrieval demo system was built to make it easy to test the retrieval performance and to expedite further algorithm investigation. And six histogram-based image retrieval methods in two color spaces were exhaustively compared by providing precision vs. recall graphs for each image class and for all test images. In general, histogram-based retrievals in HSV color space showed better performance than in RGB color space. The hitogram Intersection-based image retrieval in HSV color space was found to be most desirable among six retrieval methods.

D. Koubaroulis, et.al, "Colour-based Image Retrieval from Video Sequences", demonstrated the potential of the Multimodal Neighbourhood Signature (MNS) method for image and video retrieval. Typical region-based queries were constructed from a selection of frames from a sports video sequence of the Olympic games and retrieval results were reported. The algorithm performed well and relevant images were successfully retrieved regardless of background clutter, partial occlusion and/or non-rigid deformation. In particular, very small regions were successfully matched like the small Irish flag on the swimmer's cap. MNS signatures were computed in real-time (0.1.sec) on a Sun UltraEnterprise 450 with quad CPUs at 400 MHz and search speed was 600 image matches per second. In addition, signature size was generally small (average 900 bytes) which, combined with fast signature computation and retrieval, seems promising for demanding web-based retrieval applications. Although the MNS method supports search with illumination invariant features and use of spatial information for retrieval (e.g. for query localisation), these features were not tested in this work. Future improvements to the algorithm include introducing a training/learning stage to efficiently exploit discriminative colour characteristics inherent to the database at hand and a multi scale approach to compensate for scale changes.

Hiremath.P.S, "Content Based Image Retrieval based on Color, Texture and Shape features using Image and its complement", presents a novel framework for combining all the three i.e. color, texture and shape information, and achieve higher retrieval efficiency using image and its complement. The image and its complement are partitioned into non-overlapping tiles of equal size. The features drawn from conditional co-occurrence histograms between the image tiles and corresponding complement tiles, in RGB color space, serve as local descriptors of color

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and texture. This local information is captured for two resolutions and two grid layouts that provide different details of the same image. An integrated matching scheme, based on most similar highest priority (MSHP) principle and the adjacency matrix of a bipartite graph formed using the tiles of query and target image, is provided for matching the images. Shape information is captured in terms of edge images computed using Gradient Vector Flow fields. Invariant moments are then used to record the shape features. The combination of the color and texture features between image and its complement in conjunction with the shape features provide a robust feature set for image retrieval. The experimental results demonstrate the efficacy of the method.

Kerminen. P, “Image Retrieval Based On Color Matching”, present properties of an image retrieval system based on color matching. The implemented procedure is presented as a simplified pseudocode presentation of the system. Once histogram has been calculated and saved on the disk, it can be used for analysis.

K. Konstantinidis, “Image retrieval based on fuzzy color histogram processing”, proposed a new fuzzy linking method of color histogram creation is proposed based on the L*a*b* color space and provides a histogram which contains only 10 bins. The histogram creation method in hand was assessed based on the performances achieved in retrieving similar images from a widely diverse image collection. The experimental results prove that the proposed method is less sensitive to various changes in the images (such as lighting variations, occlusions and noise) than other methods of histogram creation.

III. PROPOSED ALGORITHM

Node The colour based Image retrieval has to be done in the way so that it will efficiently search the images from database. Colour is one of the important content of the images, so here we will work on the colour based image retrieval.

YCBCR or Y′CBCR, is a family of color spaces used as a part of the color image pipeline in video and digital photography systems. Y′ is the luma component and CB and CR are the blue-difference and red-difference chroma components. Y′ (with prime) is distinguished from Y, which is luminance, meaning that light intensity is nonlinearly encoded based on gamma corrected RGB primaries. Y′CbCr color spaces are defined by a mathematical coordinate transformation from an associated RGB color space. If the underlying RGB color space is absolute, the Y′CbCr color space is an absolute color space as well; conversely, if the RGB space is ill-defined, so is Y′CbCr. CbCr is sometimes abbreviated to YCC. Y′CbCr is often called YPbPr when used for analog component video, although the term Y′CbCr is commonly used for both systems, with or without the prime.

Y′CbCr is often confused with the YUV color space, and typically the terms YCbCr and YUV are used interchangeably, leading to some confusion; when referring to signals in video or digital form, the term "YUV" mostly means "Y′CbCr". Y′CbCr signals (prior to scaling and offsets to place the signals into digital form) are called YPbPr, and are created from the corresponding gamma-adjusted RGB (red, green and blue) source using two defined constants KB and KR as follows:

$$Y' = K_R \cdot R' + (1 - K_R - K_B) \cdot G' + K_B \cdot B'$$
$$P_B = \frac{1}{2} \cdot \frac{B' - Y'}{1 - K_B}$$
$$P_R = \frac{1}{2} \cdot \frac{R' - Y'}{1 - K_R}$$

where KB and KR are ordinarily derived from the definition of the corresponding RGB space. (The equivalent matrix manipulation is often referred to as the "color matrix".)

Here, the prime ′ symbols mean gamma correction is being used; thus R′, G′ and B′ nominally range from 0 to 1, with 0 representing the minimum intensity (e.g., for display of the color black) and 1 the maximum (e.g., for display of the color white). The resulting luma (Y) value will then have a nominal range from 0 to 1, and the chroma (PB and PR) values will have a nominal range from -0.5 to +0.5. The reverse conversion process can be readily derived by inverting the above equations.

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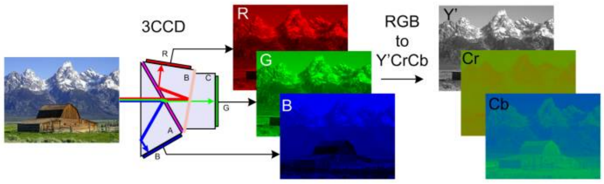

Fig. RGB to YCbCr conversion

When representing the signals in digital form, the results are scaled and rounded, and offsets are typically added. For example, the scaling and offset applied to the Y′ component per specification (e.g. MPEG-2[1]) results in the value of 16 for black and the value of 235 for white when using an 8-bit representation. The standard has 8-bit digitized versions of CB and CR scaled to a different range of 16 to 240. Consequently, rescaling by the fraction (235-16)/(240-16) = 219/224 is sometimes required when doing color matrixing or processing in YCbCr space, resulting in quantization distortions when the subsequent processing is not performed using higher bit depths.

The scaling that results in the use of a smaller range of digital values than what might appear to be desirable for representation of the nominal range of the input data allows for some "overshoot" and "undershoot" during processing without necessitating undesirable clipping. This "head-room" and "toe-room" can also be used for extension of the nominal color gamut, as specified by xvYCC.

The value 235 accommodates a maximum black-to-white overshoot of 255 - 235 = 20, or 20 / (235 - 16) = 9.1%, which is slightly larger than the theoretical maximum overshoot (Gibbs' Phenomenon) of about 8.9% of the maximum step. The toe-room is smaller, allowing only 16 / 219 = 7.3% overshoot, which is less than the theoretical maximum overshoot of 8.9%.

when Y = 0, R, G and B must all be zero, thus Cb and Cr can only be zero. Likewise, when Y = 1, R, G and B must all be 1, thus Cb and Cr can only be zero.

Unlike R, G, and B, the Y, Cb and Cr values are not independent; choosing YCbCr values arbitrarily may lead to one or more of the RGB values that are out of gamut, i.e. greater than 1.0 or less than 0.0.

The algorithm which would be proposed in the subsequent work will be based on the text and content based, which also incorporated the histogram of the image, since histogram is also one of the key in imaging field, so it will search the image not only on the basis of either colour or text, but it will search the images in the database by three factors those will be Text, colour, and Histogram of the Queried Image.

Flow of proposed work

CBIR Algorithm based on Color Histogram

1. For each image in the database Do

2. Read the image and resize it into 256x256

3. Convert RGB color space image into the desired color space (HSV, YIQ or YCbCr).

4. Divide the converted image into four blocks, each block of size 128x128.

5. Color quantization is carried out for each block using color histogram with a specified color quantization scheme that defines the size of the histogram bins for the chosen color space.

6. Normalized histogram is obtained for each block by dividing with the total number of pixels to filter the features of each block after resizing it and to be sure that contents and details of each block do not change after resizing it.

7. End For

8. Repeat Steps 2 to 6 for the query image.

9. For each image in the database Do

10. Calculate the distances between the blocks of the query image and the blocks of current image in the database and form the distance matrix .

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11. Calculate the similarity between the query image and the current image in the database based on the MSHP principle using the distance matrix,

12.End For

13. Retrieve the top 10 similar images to the query image.

Step 8: End.

IV. SIMULATION RESULTS

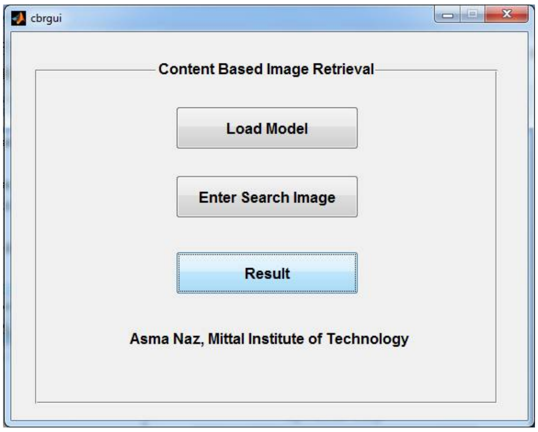

Fig 3 Main GUI for CBIR

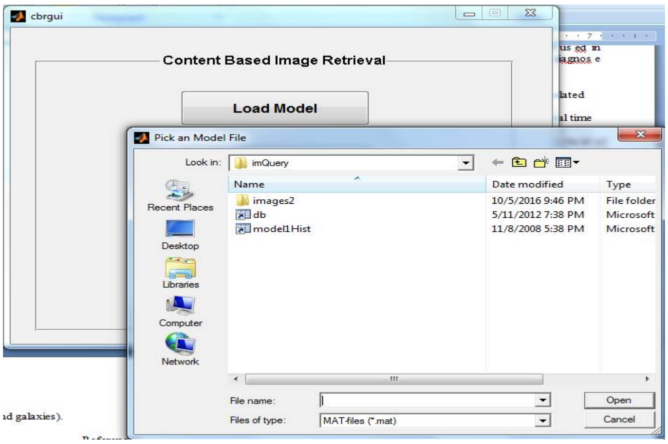

Fig 4 Load Database

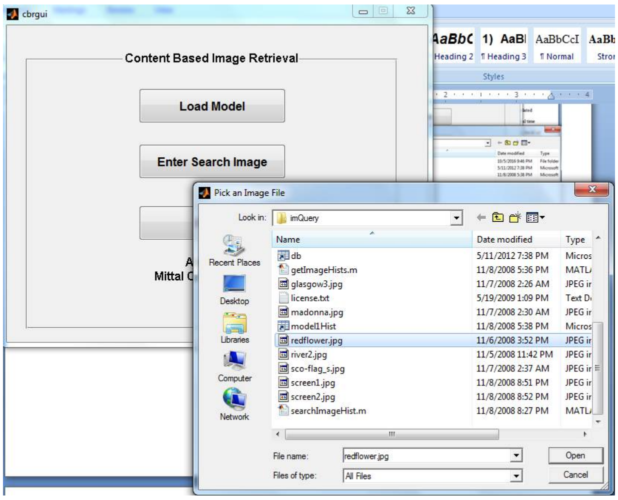

Fig 5 Choose an image

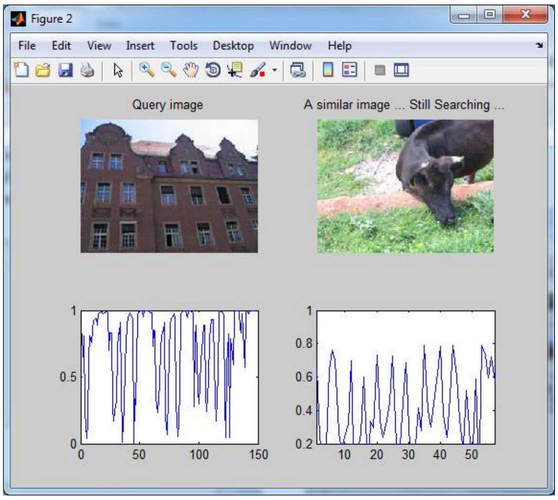

Fig 6 Similar Image

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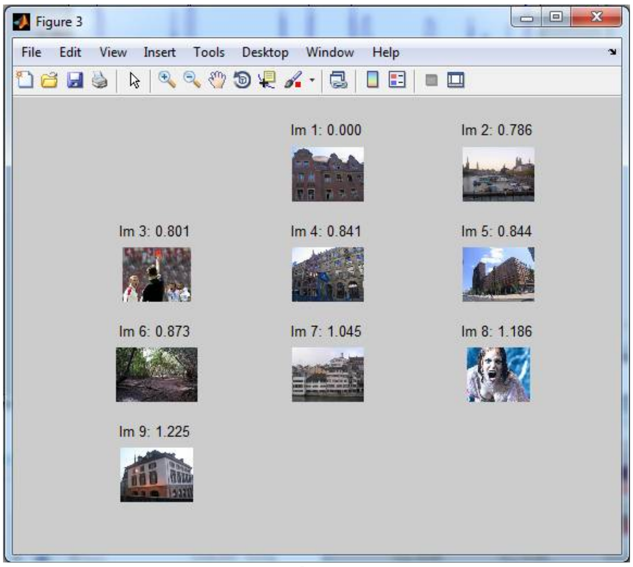

Fig 7 Similar images

Comparative Table between the Integrated approach and proposed work

	Integrated Approach	Proposed Work
Beaches	0.5	0.9
Buildings	0.7	0.9
Buses	0.98	1.0
Elephant	0.6	0.76
Flowers	0.89	0.9
Mountain	0.7	0.75
Horse	0.8	0.82
Dinosaur	1.0	1.0
Food	0.6	0.8
Overall accuracy	0.75	0.86

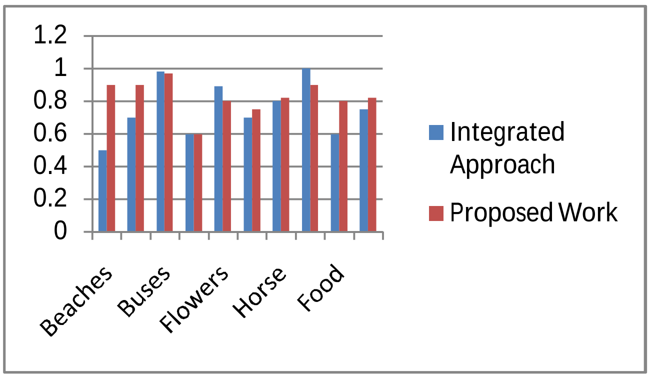

Figure 7 Precision results of Integrated approach and proposed work

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V. CONCLUSION AND FUTURE WORK

The main objective of the image mining is to remove the data loss and extracting the meaningful information to the human expected needs. The images are preprocessed with various techniques and the texture calculation is highly focus ed. Here, images are clustered based on RGB Components. Histogram is used to compare the images with some threshold constraints. This application can be used in future to classify the medical images in order to diagnose the right disease verified earlier.

This system is useful in future to detect the diseases related with human. More effort to be taken to reduce the Image retrieval time of a given input Query Image.

In future this system is also implemented in the field of computer Vision which is concerned with the automated processing of images from the real world to extract and interpret information on a real time basis. In future these System is used in Astronomy to the study of celestial objects (such as stars , planets , comets , nebulae, star clusters and galaxies).

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