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RETRIEVING AN IMAGE USING CBIR

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Abstract - The aim of this paper is to review the present state of the art of content based image retrieval. Retrieval of an image is a more effective and efficient for managing extensive image database. Content Based Image Retrieval (CBIR) is a one of the image retrieval technique which uses user visual features of an image such as color, shape, and texture features etc. It permits the end user to give a query image in order to retrieve the stored images in database according to their similarity to the query image. But the proper selection of feature are challenging task of classification Euclidean distance is used in retrieving the similar images. In this work, content based image retrieval is accomplished by combining the two features such as color and texture. Color features are extracted by using hsv histogram, color auto correlogram and color moment values. Texture feature extraction used Grey Level Co-occurrence Matrix (GLCM) and Color Co-occurrence matrix (CCM).In CCM method, three approaches are used. In the first approach CCM is calculated from whole image. In second approach divided the image into sub-blocks of equal size and CCM matrix is calculated from sub-block of one channel and corresponding sub-block of other channel by considering each sub-block as the separate image.

Keywords*: content based image retrieval, S.V.M classifier, Color Histogram, Query Image, RGB Color model, Co-occurrence model*

I. INTRODUCTION

Digital images are used in a wide range of applications such as geography, medical, architecture, advertising, design, military and albums. A huge amount of information is out there. However, we cannot access or make use of the information unless it is organized so as to allow efficient browsing, searching, and retrieval. Traditional methods of image indexing have been proven neither suitable nor efficient in terms of space and time so it triggered the development of the new technique. The query concept is typically semantic while the features that can be currently extracted from general databases are mostly visual and lower level.

"Content based" refers that the search will analyse the contents of an image rather than the data about image such as keywords, tags, name of file extension like jpg, bmp, gif etc. Here the „*content*" refers visual information's such as color, texture and shape that can be derived from the image itself. The users generally prepare query image and present to the system. The system automatically extract the visual attributes of the query image in the same mode as it does for each database image and then identifies images in the database whose feature vectors match those of the query image, and sorts the best similar objects according to

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their similarity value. CBIR is cheap, fast and efficient advantage over text based retrieval. CBIR system can be used in one of the two ways. First, exact image matching, that is matching two images, one an example image and the other, image in image database. Furthermore is approximate image matching, which is finding most closely match images to a query image. The content based image retrieval techniques aim to respond to a query image with query similar resultant images obtained from the image database. This paper is aimed at minimizing the time required for the retrieval of desired images from the database with improved accuracy by using support vector machine (SVM).So, in this paper, we present a technique for image retrieval based on local color and texture features.

II. LITERATURE SURVEY

An image (from Latin: imago) is an artefact, for example a two dimensional picture, that has a similar appearance to some subject—usually a physical object or a person. Images may be two-dimensional, such as a photograph, screen display, and as well as a three-dimensional, such as a statue or hologram. They may be captured by optical devices—such as cameras, mirrors, lenses, telescopes, microscopes, etc. and natural objects and phenomena, such as the human eye or water surfaces. The word image is also used in the broader sense of any two-dimensional figure such as a map, a graph, a pie chart, or an abstract painting. In this wider sense, images can also be rendered manually, such as by drawing, painting, carving, rendered automatically by printing or computer graphics technology, or developed by a combination of methods, especially in a pseudo-photograph.

2.1 CLASSIFICATION METHODS

Image classification is a method to label an image with appropriate identifiers. These identifiers are determined by the area of interest, to see whether it is general classification for a specific domain or arbitrary pictures

Color Feature

Color feature is one of the most common and most widely used features in the image retrieval and classification tasks. In this Project, we use color histogram which in HSV color space as color feature. HSV color space attempts to describe perceptual color relationship more accurately than RGB space, while remaining computationally simple. The H, S, V stands for hue, saturation and value separately. A histogram of an image is produced first by discretization of the colors in the image into a number of bins, and counting the number of image pixels in each bin. In our method, we quantize H, S, and V into 16, 4, and 4 bins, therefore we can get a 256 dimensional color feature vector. Though the images are classified in the same class by human, their color histograms are different obviously. It means that in the low-level space, they are not in the same class.

Texture Feature

Texture is another important property of images. Texture is a powerful regional descriptor that helps in the retrieval process. Texture, on its own does not have the capability of finding similar images, but it can be used to classify textured images from non-textured ones and then be combined with another visual attribute like color to make t*he retrieval more effective. Texture has been one of the most important characteristic which has been used to classify and recognize objects and have been used in finding similarities between images in multimedia databases. Texture features typically consist of contrast, uniformity, coarseness, and density. Importance of the texture feature is due to its presence in many real world images: for example, clouds, trees, bricks, hair, fabric etc., all of which have textural characteristics

Basically, texture representation methods can be classified into two categories: structural; and statistical. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura features, World decomposition, Markov random field, fractal model

Shape feature

Shape based image retrieval is the measuring of similarity between shapes represented by their features. Shape is an important visual feature and it is one of the primitive features for image content description. Shape content description is difficult to define because measuring the similarity between shapes is difficult. Therefore, two steps are essential in shape based image retrieval, they are: feature extraction and similarity measurement between the extracted features. Shape descriptors can be divided into two main categories: region based and contour-based methods. Region-based methods use the whole area of an object for shape description, while contour-based methods use only the information present in the contour of an object.

Support Vector Machine (SVM)

SVMs are supervised learning methods used for image classification. It views the given image database as two sets of vectors in an ‘ n ’dimensional space and constructs a separating hyper plane that maximizes the margin between the images relevant to query and the images not relevant to the query. SVM is a kernel method and the kernel function used in SVM is very crucial in determining the performance.

The basic principle of SVMs is a maximum margin classifier. Using the kernel methods, the data can be first implicitly mapped to a high dimensional kernel space. The maximum margin classifier is determined in the kernel space and the corresponding decision function in the original space can be non-linear. The non-linear data in the feature space is classified into linear data in kernel space by the SVMs. This is illustrated in Figure 1 as follows.

The aim of SVM classification method is to find an optimal hyper plane separating relevant and irrelevant vectors by maximizing the size of the margin (between both classes)

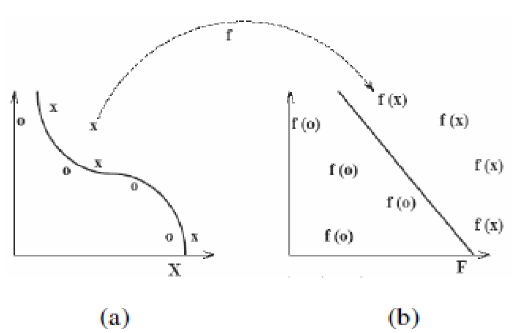

Figure 1.How the function ‘f’ embeds the data in the original space

III. AIM AND OBJECTIVE

The aim of this project is to review the current state of the art in content-based image retrieval (CBIR), a technique for retrieving images on the basis of automatically-derived features such as color, texture and shape. Findings are based both on a review of the relevant literature and on discussions with researchers in the field. The need to find a desired image from a collection is shared by many professional groups, including journalists, design engineers and art historians.

Objective

- More accurate the data more accurate the result.

- Implemented the CBIR system which takes into consideration the low level features of image which is more comprehensive when compared to high level features and it also gives user a higher level of retrieval

- User always wants a friendly environment so that they can easily and effectively use the system without actually going into the finer details of the working.

- So, to create such a user friendly platform for the system designed a Graphic User Interface where user can actually select the method which they want to be used for the image retrieval and that will give them an option of using different method if the result is not as per their requirement

- Objective here is not only to have correct prediction for color, texture but also to predict a background color and image.

IV. STAGES IN PROPOSED SYSTEM

4.1 COLOR HISTOGRAM

A color histogram is a image of the distribution of colors in an image For digital images, a color histogram represents the number of pixels that have colors in each of a fixed list of color ranges that span the image's color space, the set of all possible colors. In spite of the fact that the color histogram technique is a very simple and low-level method, it has shown good results in practice especially for image indexing and retrieval tasks, where feature extraction has to be as simple and as fast as possible. Spatial features are lost, meaning that spatial relations between parts of an image cannot be used. This also ensures full translation and rotation invariance. A color is represented by a three dimensional vector corresponding to a position in a color space. This leaves us to select the color space and the quantization steps in this color space. As a color space, chose the hue-saturation-value (HSV) space, which is in bijection with the red–green–blue (RGB) space. The reason for the choice of HSV is that it is widely used in the literature. HSV is attractive in theory. It is considered more suitable since it separates the color components (HS) from the luminance component (V) and is less sensitive to illumination changes. Note also that distances in the HSV space correspond to perceptual differences in color in a more consistent way than in the RGB space.

However, this does not seem to matter in practice. All the experiments reported in the paper use the HSV space. For the sake of comparison, have selected a few experiments and used the RGB space instead of the HSV space, while keeping the other conditions identical: the impact of the choice of the color space on performance was found to be minimal compared to the impacts of the other experimental conditions (choice of the kernel, remapping of the input).An explanation for this fact is that, after quantization into bins, no information about the color space is used by the classifier. The number of bins per color component has been fixed to 16, and the dimension of each histogram is . Some experiments with a smaller number of bins have been undertaken, but the best results have been reached with 16 bins. Have not tried to increase this number, because it is computationally too intensive.

It is preferable to compute the histogram from the highest spatial resolution available. Subsampling the image too much results in significant losses in performance. This may be explained by the fact that by subsampling, the histogram loses its sharp peaks, as pixel colors turn into averages (aliasing).

A. COLOR AUTO CORRELOGRAM

Color Auto correlogram have been shown to excel color histograms, color coherence vectors and color co-occurrence matrices when used as feature vectors in CBIR system. This is due mainly to their skills to detect the spatial relation of colours. In this work show that future improvement in the performance of Auto correlogram can be achieved by choosing an appropriate color space. Specifically when robustness to illumination condition changes is an issue, HSV color space has been proven to be a good choice to work with. Performance variations due to distance matrices and image database size are also considered.

B. COLOR MOMENTS

Color moments are measures that can be used differentiate images based on their features of colors. Once calculated these moments provide a measurement for color similarity between images. These values of similarity can then be compared to the values of images indexed in a database for tasks like image retrieval. The basis of color moments lays in the assumption that the distribution of color in an image can be interpreted as a probability distribution. Probability distribution can be characterized by a number of unique moments. it therefore follows that if the color of an image follows a certain probability distribution ,the moments of that distribution can then be used as features to identify that image based on color.

C. WAVELET TRANSFORM

The wavelet transform provides an appropriate basis for image handling because of its beneficial features. The assets of the wavelet transform are:

1. The ability to compact most of the signal's energy into a few transformation coefficients, which is called energy compaction.

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2. The ability to capture and represent effectively low frequency components(such as image backgrounds) as well as high frequency transients (such as image edges).
3. The variable resolution decomposition with almost uncorrelated coefficients.

D. GABOR WAVELET TRANSFORM

It is invented by Dennis Gabor. Wavelet transform could perform multi-resolution time-frequency analysis. The tunable kernel size results in different time-frequency resolution pair and the size is related to the analytical frequency. For example, smaller kernel size (in time domain) has higher resolution in time domain but lower resolution in frequency domain, and is used for higher frequency analysis; while bigger kernel size has higher resolution in frequency domain but lower resolution in time domain, and is used for lower frequency analysis. This great property makes wavelet transform suitable for applications such as image compression, edge detection, filter design, and some kinds of image object recognition, etc. Among various wavelet bases, Gabor functions provide the optimal resolution in both the time (spatial) and frequency domains, and the Gabor wavelet transform seems to be the optimal basis to extract local features.

V. ALGORITHMS IMPLEMENTATION

A. CCM ALGORITHM

Original image is coded into Red, Green and Blue channel, and then the color co-occurrence matrix between any two channels (Cu, Cv) is obtained as follows:

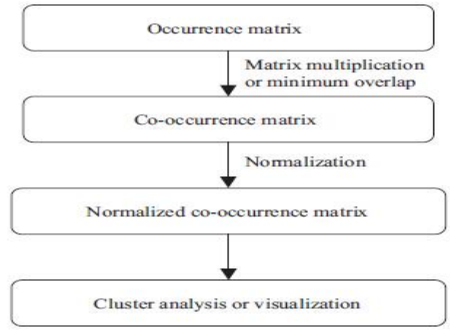

Fig 2:- CCM algorithm

$$c(i,j)=\sum_{x=1}^{n}\sum_{y=1}^{m}\begin{cases}1 \text{ if } cu(x,y)=i \text{ and } cv(x+t,y+t)=j\\ 0 \text{ otherwise}\end{cases}$$

With one matrix per couple of channels(C, C)

B. HSV ALGORITHM

RGB to HSV conversion in figure, the obtainable HSV colors lie within a triangle whose vertices are defined by the three primary colors in RGB space.

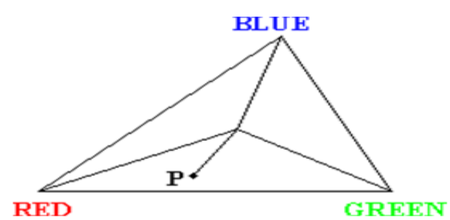

Fig 3:-HSV Algorithm

The hue of the point P is the measured angle between the line connecting P to the triangle center and line connecting RED point to the triangle center. The saturation of the point P is the distance between P and triangle center. The value (intensity) of the point P is represented as height on a line perpendicular to the triangle and passing through its center. The grayscale points are situated onto the same line. Conversion formula for HSV.

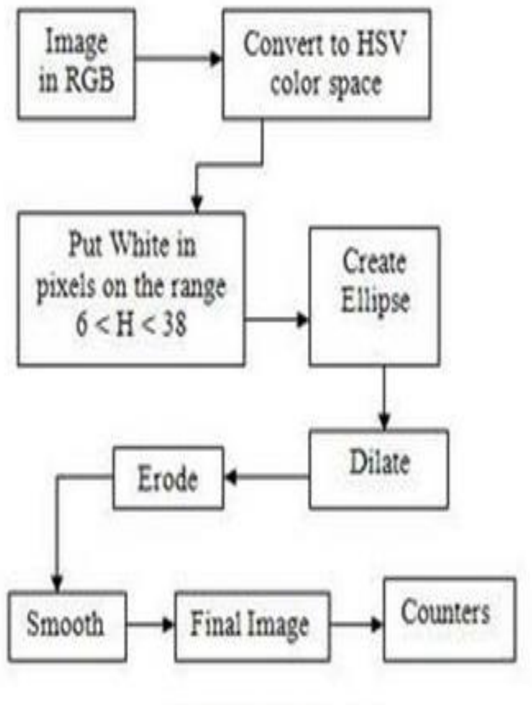

Fig 4: –HSV Algo diagram

$$H = \cos^{-1}\frac{\frac{1}{2}[(R-G)+(R-G)]}{\sqrt{(R-G)^2+(R-G)(R-G)}}$$

$$S = 1-\frac{3}{R+G+B}[\min(R,G,B)].$$

$$V = \frac{1}{3}(R+G+B)$$

VI. SYSTEM ARCHITECTURE

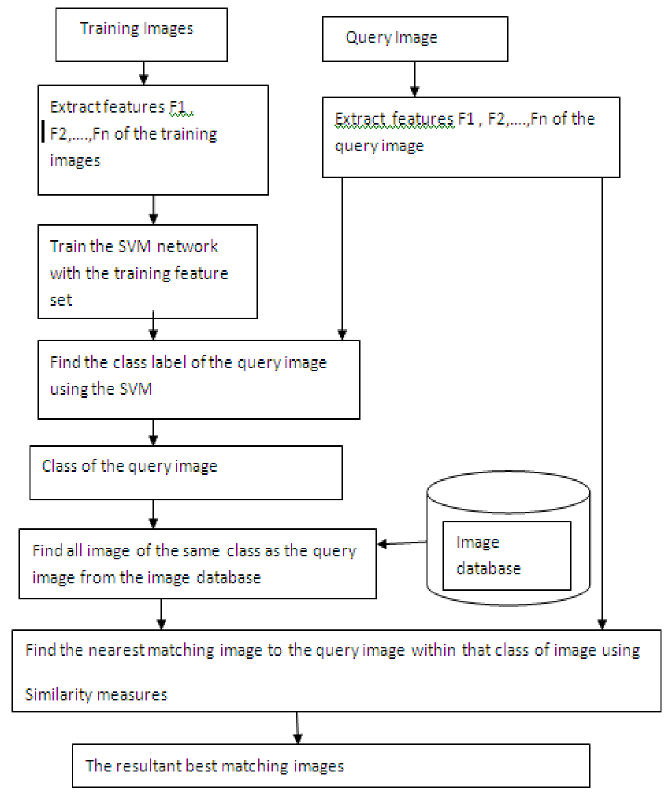

Fig5: - System Architecture

VII.EXPECTED OUTPUT

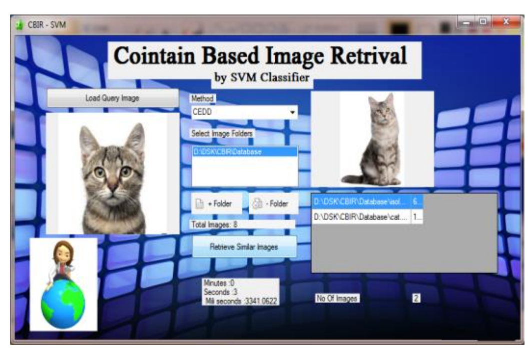

Fig6:- Expected Output

VIII. CONCLUSIONS

The extent to which CBIR technology is currently in routine use is clearly still very limited. In particular, CBIR technology has so far had little impact on the more general applications of image searching, such as journalism or home entertainment.

Only in very specialist areas such as crime prevention has CBIR technology been adopted to any significant extent. This is no coincidence while the problems of image retrieval in a general context have not yet been satisfactorily solved, the well-known artificial intelligence principle of exploiting natural constraints has been successfully adopted by system designers working within restricted domains where shape, color or texture features play an important part in retrieval.

REFERENCES

[1] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, and R Jain*, "Content-based image retrieval at the end of the early years,"* IEEETrans. Pattern Anal. Mach. Intell., vol. 22, no. 12, pp. 1349–1380, Dec.2000.

[2] Y. Rui, T. S. Huang, M. Ortega, and S. Mehrotra, "Relevance feedback power tool for interactive content-based image retrieval," IEEETrans. Circuits Syst. Video Technol., vol. 8, no. 5, pp. 644–655, Sep.1998.

[3] C. D. Manning, P. Raghavan, and H. Schutze, Introduction to Information Retrieval. Cambridge, U.K.: Cambridge Univ Press, 2008.

[4] K. Tieu and P. Viola, *"Boosting image retrieval*," Int. J Comput. Vis.,vol. 56, no. 1/2, pp. 17–36, 2004.

[5] X. He, O. King, W.-Y. Ma, M. Li, and H.-J. Zhang, "*Learningasemanticspace* from user's relevance feedback for image".

[6] H.B.Kekre, Sudeep D. Thepade, *"Image Retrieval using Augmented Block Truncation Coding Techniques*", ACM International Conference on Advances in Computing, Communication and Control (JCAC3-2009), pp. 384-390, 23-24

7] Minh N. Do, Martin Vetterli, *"Wavelet-Based Texture Retrieval Using Generalized Gaussian Density and Kullback-LeiblerDistance"*, IEEE Transactions on Image Processing, Volume II, Number 2, pp.146-158, February 2002.

[8]B.G.Prasad, K.K. Biswas, and S. K. Gupta, *"Region -based image retrieval using integrated color, shape, and location index"*, International Journal on Computer Vision and Image Understanding Special Issue: Colour for Image Indexing and Retrieval,Volume 94, Issues 1-3, April-June 2004, pp.I93-233.

[9]H.B.Kekre, TanujaSarode, Sudeep D. Thepade, *"OCT Applied to Row Mean and Column Vectors in Fingerprint Identification"*, In Proceedings of International Conference on Computer Networks and Security (ICCNS), 27-28 Sept. 2008, VIT, Pune.

[10]Zhibin Pan, Kotani K., Ohmi T., *"Enhanced fast encoding method for vector quantization by finding an optimally-ordered Walsh transform kernel*", ICIP 2005, IEEE International Conference, Volume I, pp I - 573-6, Sept. 2005.

