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IMAGE RETRIEVAL BY USING DIGITAL IMAGE PROCESSING AND GA

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ABSTRACT

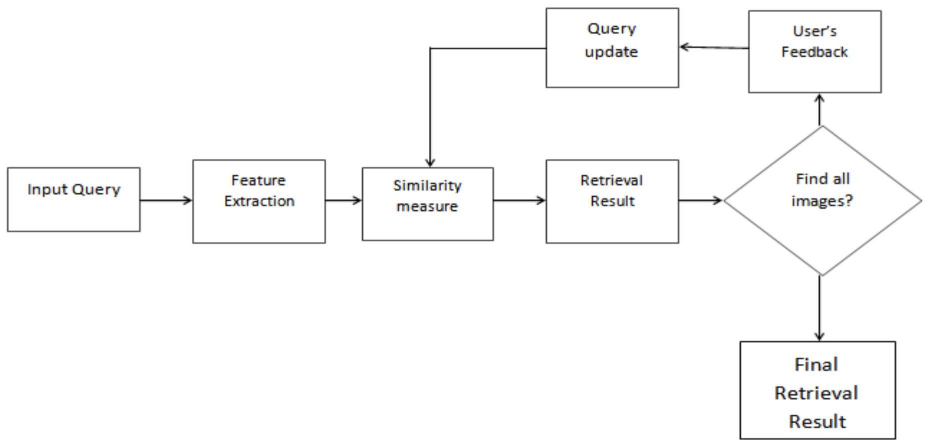
In recent years, with the development of digital image techniques and digital albums in the Internet, the use of digital image retrieval process has increased dramatically. An image retrieval system is a computer system for browsing, searching and retrieving images from large databases of digital images. In order to increase the accuracy of image retrieval, a intent-based image retrieval system(IBIR) based on interactive genetic algorithm (IGA) is proposed. Color, texture and edge have been the primitive low level image descriptors in content based image retrieval systems. In this paper we proposed a system that splits the retrieval process into two stages. In the query stage, the feature descriptors of a query image were extracted and then used to evaluate the similarity between the query image and those images in the database. In the evolution stage, the most relevant images were retrieved by using the IGA. IGA is employed to help the users identify the images that are most satisfied to the users' need.

1. INTRODUCTION

Image retrieval techniques are useful in many image-processing applications. Content-based image retrieval systems work with whole images and searching is based on comparison of the query. General techniques for image retrieval are color, texture and shape. These techniques are applied to get an image from the image database. They are not concerned with the various resolutions of the images, size and spatial color distribution. Hence all these methods are not appropriate to the art image retrieval. Moreover shape based retrievals are useful only in the limited domain. The content and metadata based system gives images using an effective image retrieval technique. Many Image retrieval techniques are useful in many image-processing applications. Content-based image retrieval systems work with whole images and searching is based on comparison of the query. General techniques for image retrieval are color, texture and shape. These techniques are applied to get an image from the image database. They are not concerned with the various resolutions of the images, size and spatial color distribution. Hence all these methods are not appropriate to the art image retrieval. Moreover shape based retrievals are useful only in the limited domain. The content and metadata other image retrieval systems use global features like color, shape and texture. But the prior results say there are too many false positives while using those global features to search for similar images. Hence we give the new view of image retrieval system using both content and metadata.

Background: The Growth of Digital Imaging

The use of images in human communication is hardly new -our cave-dwelling ancestors painted pictures on the walls of their caves, and the use of maps and building plans to convey information almost certainly dates back to preRoman times. But the twentieth century has witnessed unparalleled growth in the number, availability and importance of images in all walks of life. Images now play a crucial role in fields as diverse as medicine, journalism, advertising, design, education and entertainment. Technology, in the form of inventions such as photography and television, has played a major role in facilitating the capture and communication of image data. But the real engine of the imaging revolution has been the computer, bringing with it a range of techniques for digital image capture, processing, storage and transmission which would surely have startled even pioneers like John Logie Baird. The involvement of computers in imaging can be dated back to 1965, with Ivan Sutherland's Sketchpad project, which demonstrated the feasibility of computerized creation, manipulation and storage of images, though the high cost of hardware limited their use until the mid-1980s. Once computerized imaging became affordable (thanks largely to the development of a mass market for computer games), it soon penetrated into areas traditionally depending heavily on images for communication, such as engineering, architecture and medicine. Photograph libraries, art galleries and museums, too, began to see the advantages of making their collections available in electronic form. The creation of the World-Wide Web in the early 1990s, enabling users to access data in a variety of media from anywhere on the planet, has provided a further massive stimulus to the exploitation of digital images. The number of images available on the Web was recently estimated to be between 10 and 30 million [Sclaroff et al, 1997] – a figure in which some observers consider to be a significant underestimate.



2. RELATED WORK

An image is worth more than ten thousand words. Human beings are able to explain a narrative from an image on the basis of observations and specifically their background knowledge. One important question that arises is whether it can be develop an intelligent model to learn image concepts like human. There is no doubt that the ambitious efforts have been made to develop an intelligent model in the past decade. The most straightforward form of image retrieval systems, simply asks the user to specify one or more relevant images. To improve the query results, some systems allow the user to manually change the weight of image features [2]. This gives higher weights to features in which example images are similar and gives lower weights to those features where the images differ. Some systems allow the users to specify irrelevant images as negative examples. This approach, however, introduces undesirable side effects because it tries to cluster negative examples into one class. In actuality, negative examples can be many classes of images in the database. There are some literatures that survey the most important CBIR systems [6]. Also, there are some papers that overview and compare the current techniques in this area [7]. Since the early studies on CBIR, various color descriptors have been adopted. Yoo et. al. [8] proposed a signature-based color-spatial image retrieval system. Different type of color spaces and its spatial distribution within the image are used for the features. In [9], a CBIR scheme based on the global and local color distributions in an image is presented. Vadivel et. al. [10] have introduced an integrated approach for capturing spatial variation of both color and intensity levels and shown its usefulness in image retrieval applications. Like color, texture is also an important visual feature in defining high level semantics for image retrieval purposes. Wavelet based texture evaluation using subbands by bit-plane extractions in texture image retrieval were presented in [11]. An effective and efficient characterization to overcome some limitations, such as computational expensive approaches or poor retrieval accuracy, in a few texture based image retrieval methods, Kokare et. al. [12] concentrated on the problem of finding good texture features for CBIR. Pi and Li [13] combined fractal parameters and collage error to propose a set of new statistical fractal signatures. These signatures effectively extract the statistical properties intrinsic in texture images to enhance retrieval rate. Liapis and Tziritas [14] explored image retrieval mechanisms based on a combination of texture and color features. Texture features are extracted using discrete wavelet frame analysis. One or two dimensional histograms of the CIE Lab chromaticity coordinates are used as color features. Chun et al. [15] proposed a CBIR method based on an efficient combination of multiresolution color and texture features. As its color features, color autocorrelograms of the hue and saturation component images in HSV color space are used. The color and texture features are extracted in multiresolution wavelet domain and then combined. In order to well model the high-level concepts in an image and user's subjectivity, recent approaches introduce human computer interaction into CBIR. Takagi et. al. [4] evaluated the performance of the similarity based GAbased image retrieval system that uses wavelet coefficients to represent physical features of images. Cho et. al. [16] applied GA to solve the problems of emotion based image retrieval. He used wavelet transform to extract image features and IGA to search the image that the user has in mind. When the user gives appropriate fitness to what he or she wants, the system provides the images selected based on the user's evaluation. In [17], a new GA framework incorporating relevance feedback for image retrieval was proposed. Some technique combines an GA with an extended nearest neighbor approach to reduce the existing gap between the high-level semantic contents of images and the information provided by their low level descriptors. Shi et al. [22] proposed GA-based approach which incorporates an adjust function and a SVM. Their method can prevent the optimal solution from losing, accelerate the convergence of GA, and raise retrieval performance. To reduce the gap between the retrieval results and the users' expectation, the IGA [19] is employed to help the users identify the images that are most satisfied to the users' need.

3. METHODOLOGY

In this for effective execution of the task we considered the visual features from images, the color descriptor and texture descriptor are helpful for performing the task of image retrieval. Color Descriptor: The human eyes cannot distinguish the colors very efficiently. The colors can be divided into 8 parts and saturation and intensity into 3 parts separately. As per the quantization levels, the HSV three dimensional feature vector for different values of with different weight to form one-dimensional feature vector named G[7]: G=QsQvH+QvS+V. Where Qs is quantified series of S. Qv is quantified series of V. We can set Qs=Qv=3 , G=9H+3S+V.

$$H=\begin{cases} 0 \text{ if } h\in[316,20] \\ 1 \text{ if } h\in[21,40] \\ 2 \text{ if } h\in[41,75] \\ 3 \text{ if } h\in[76,155] \\ 4 \text{ if } h\in[156,190] \\ 5 \text{ if } h\in[191,270] \\ 6 \text{ if } h\in[271,295] \\ 7 \text{ if } h\in[296,315] \end{cases}$$

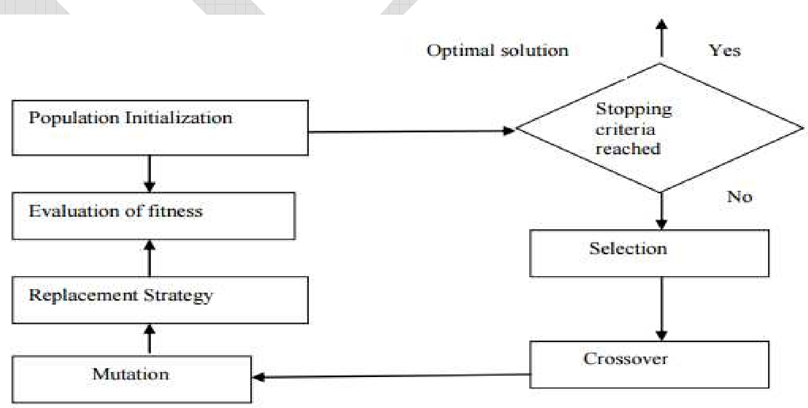
$$S=\begin{cases} 0 \text{ if } s\in[0,0.2] \\ 1 \text{ if } s\in[0.2,0.7] \\ 2 \text{ if } s\in[0.7,1] \end{cases}$$

$$V=\begin{cases} 0 \text{ if } v\in[0,0.2] \\ 1 \text{ if } v\in[0.2,0.7] \\ 2 \text{ if } v\in[0.7,1] \end{cases}$$

Here we can thus have 72 bins of one-directional histogram [6]. This reduces the complexity and time computation. The role of color cumulative histogram, in this the color histogram is derived by first quantize colors in the image into a number of bins in a specific color space and counting number of bins in each bin. In this, when characteristics of images should not take over all the values, the statistical histogram will appear in a number of zero values. This may leads to not accurately reflect the color difference between images. Therefore here needs to construct a cumulative histogram of the color characteristics of image after using non-interval HSV quantization for G[6]. Texture Descriptor: Now the texture feature extraction which can be done with the help of GLCM and CCM. The gray level co-occurrence matrix (GLCM) creates a matrix with the directions and distances between pixels and then extracts meaningful statistics from the matrix as texture features. The GLCM composed of probability value given by, is taken into account. The element in theθ) where between two pixels the distance d and direction in θ d , | P (i , j matrix are computed as,

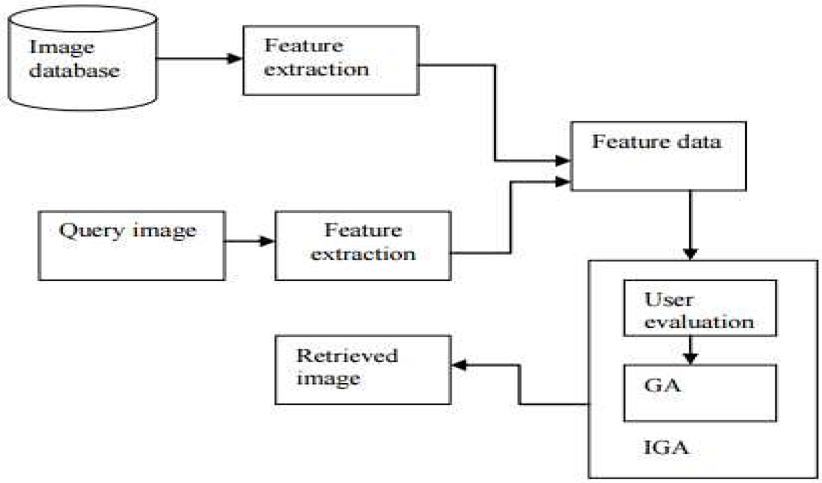
$$P(i,j \mid d,\theta) = \frac{P(i,j \mid d,\theta)}{\sum_i \sum_j P(i,j \mid d,\theta)}$$

IGA: The methodology is mostly depending on the low level feature extraction in an image and then after processing them the application of IGA to it. The use of Genetic Algorithm includes some steps as, making certain set of solutions represented by chromosomes which then called population. Solutions from one population are taken which then forms another population. In this way better population would forms and new desired offspring are also forms as per the fitness functions. The very first thing is to generate the population of n chromosomes ,then evaluation of the of fitness function of each chromosome in the populations. Repeat the process for creation of new population until the new population is complete. Initialization :Here the individual solutions are to be formed which then forms initial population. Nature of problem will decide the size of it, which contains large number of possible solutions. The "seeding" of solution is to be made where the chances of finding the optimal solutions. Selection: During each successive generation, a part of existing population is used for breeding the newer one. Then proper fitter fitness function is selected. The fitness function is always problem dependent. Further taking Genetic Operators into consideration as, Crossover and Mutation: From these crossover and mutation operators the second and likely more population generations would be taken place. For each new solution to be produced, a pair of parent solution is required which are already selected previously. By producing child solution from crossover and mutation methods, the characteristics of parent would be shared. New parents are selected for each new "child", and the process continues until a new population of solutions of appropriate size is generated [3]. These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions. These less fit solutions ensure genetic diversity within the genetic pool of the parents and therefore ensure the genetic diversity of the subsequent generation of children. It is worth tuning parameters such as the mutation probability, crossover probability and population size to find reasonable settings for the problem class being worked on. If mutation rate is small then leads to genetic drift. If mutation rate is too high may lead to loss of good solutions unless there is elitist selection .If recombination rate is too high then it leads to premature convergence of the genetic algorithm. Termination: This generational process is repeated until a termination condition has been reached. There might be some conditions for this



Overview of Genetic Algorithm

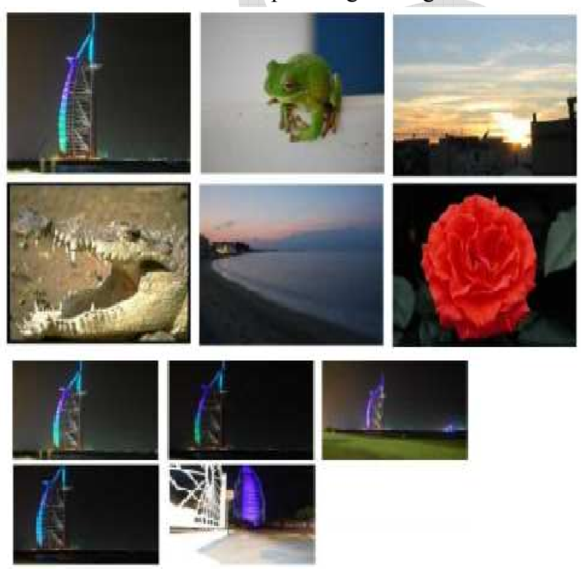
There are the steps for genetic algorithm which are explained earlier and also shown in the flowchart above fig 1. Now the system flowchart is also shown below where the query image can be drawn from database and also its feature extraction would be done. After extracting the features from image the GA to be applied, but instead of that the novel approach of IGA is preferred[4]. The main difference between IGA and GA is the construction of the fitness function, i.e., the fitness is determined by the user"s evaluation and not by the predefined mathematical formula. A user can interactively determine which members of the population will reproduce, and IGA automatically generates the next generation of content based on the user"s input. By repeating content generation and fitness assignment, IGA enables unique content to evolve that suits the user"s preferences.



System flowchart

4. EXPERIMENTAL RESULT

The effectiveness of this system is shown here with retrieval of the images, for this a suitable database is selected. In this we selected a database which covers a wide range of images; we are having 5 – 6 categories of images which are differing from each others. The sample images are given in



5. CONCLUSION

This paper gives one of the effective retrieval method in CBIR, where the use of IGA gives efficient and accurate results in contrast to the conventional approaches that are based on visual features, the IGA method provides an interactive mechanism to bridge the gap between visual features & human perception. The color information of an image & entropy in addition with texture descriptor using GLCM gives vital help in characterizing the image. As these features & performances of IGA approach to image retrieval lifts up a task of CBIR at more significant level.

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