International Journal of Engineering Science Invention (IJESI)
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org ||Volume 7 Issue 2|| February 2018 || PP. 32-38

Content Based Image Retrieval Based On Internal Regions Using Clustering Methods in Interactive Genetic Algorithm

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Abstract— *Content Based Image Retrieval (CBIR) is a way to extend and improve query methods for searching the image in databases. In CBIR, a description of the required content in terms of visual features of an image is required. Images can then be ranked with respect to their similarity to the description. Extracting required textual information manually or automatically has been a relatively simple task. However, when the information is held as an image, the same is a hard task. Though, the human can interpret and teach the characteristics of the image to a machine are possible. The Proposed work focuses on two methods: 1) Interactive Genetic Algorithm and 2) Image Features. In IGA the search process is repeated until the user satisfies with the result. The image features is of color, edge and texture descriptor. This is done by using the low-level descriptions.*
Index Terms—*Content-based image retrieval (CBIR), human– machine interaction, interactive Genetic Algorithm (GA) (IGA), low-level descriptors.*

Date of Submission: 22-01-2018 Date of acceptance: 12-02-2018

I. Introduction

In recent years, rapid advances in science and technology have produced a large amount of image data in diverse areas, such as entertainment, art galleries, fashion design, education, medicine, industry, etc. We often need to efficiently store and retrieve image data to perform assigned tasks and to make a decision. Therefore, developing proper tools for the retrieval Image from large image collections is challenging. Two different types of approaches, i.e., text- and content- based, are usually adopted in image retrieval. In the text-based system, the images are manually annotated by text descriptors and then used by a database management system to perform image retrieval. However, there are two limitations of using keywords to achieve image retrieval: the vast amount of labor required in manual image annotation and the task of describing image content is highly subjective. That is, the perspective of textual descriptions given by an annotator could be different from the perspective of a user. In other words, there are inconsistencies between user textual queries and image annotations or descriptions. To alleviate the inconsistency problem, the image retrieval is carried out according to the image contents. Such strategy is the so-called content-based image retrieval (CBIR). The primary goal of the CBIR system is to construct meaningful descriptions of physical attributes from images to facilitate efficient and effective retrieval [1], [2].

Ever since the day CBIR emerged, it has been considered as a gold mine with the potential to change the way people search information. Using text for image retrieval is a mature technology, but in many cases, it is hard to get precise semantic description of what people search for. Initially, developed algorithms exploit the low-level features of the image such as color, texture, and shape of an object to help retrieve images. They are easy to implement and perform well for images that are either simple or contain few semantic contents. However, the semantics of an image are difficult to be revealed by the visual features, and these algorithms have many limitations when dealing with broad content image database. Therefore, in order to improve the retrieval accuracy of CBIR systems, region- based image retrieval methods via image segmentation were introduced. These methods attempt to overcome the drawbacks of global features by representing images at object level, which is intended to be close to the perception of human visual system. However, the performance of these methods mainly relies on the results of segmentation.

The difference between the user's information need and the image representation is called the semantic gap in CBIR systems. The limited retrieval accuracy of image centric retrieval systems is essentially due to the inherent semantic gap. In order to reduce the gap, the interactive relevance feedback is introduced into CBIR. The basic idea behind relevance feedback is to incorporate human perception subjectivity into the query process and provide users with the opportunity to evaluate the retrieval results. The similarity measures are automatically refined on the basis of these evaluations. However, although relevance feedback can significantly improve the retrieval performance, its applicability still suffers from a few drawbacks [3]. The semantic-based image retrieval methods try to discover the real semantic meaning of an image and use it to retrieve relevant images. However, understanding and discovering the semantics of a piece of information are high- level cognitive tasks and thus hard to automate. A wide variety of CBIR algorithms has been proposed, but most of them focus on the similarity computation phase to efficiently find a specific image or a group of images that are similar to the given query. In order to achieve a better Approximation of the user's information need for the following search in the image database, involving user's interaction is necessary for a CBIR system. In this paper, we propose a user-oriented CBIR system that uses the interactive genetic algorithm (GA) (IGA) [5] to infer which images in the data- bases would be of most interest to the user. Three visual features, color, texture, and edge, of an image is utilized in our approach. IGA provides an interactive mechanism to better capture user's intention. There are very few CBIR systems considering human's knowledge, but [6] is the representative one. They considered the red, green, and blue (RGB) color model and wavelet coefficients to extract image features. In their system, the query procedure is based on association (e.g., the user browses an image collection to choose the most suitable ones). The main properties of this paper that are different from it can be identified as follows: 1) low-level image features—color features from the hue, saturation, value (HSV) color space, as well as texture and edge descriptors, are adopted in our approach and 2) search technique—our system adopts the query-by-example strategy (i.e., the user provides an image query).

The remainder of this paper is organized as follows. Related works about CBIR are briefly reviewed in Section II. Section III describes the considered image features and the concept of IGA. The proposed approach is presented in Section IV. Section V gives the experimental results and provides comparative performances. Finally, Section VI presents the conclusions of this paper.

II. Related Previous Works

There are some literatures that survey the most important CBIR systems [7], [8]. Also, there are some papers that overview and compare the current techniques in this area [9], [10]. Since the early studies on CBIR, various color features have been adopted. In [12], a CBIR scheme based on the global and local color distributions in an image is presented. Vadivel *et al.* [13] have introduced an integrated approach for capturing spatial variation of both color and intensity levels and shown its usefulness in image retrieval applications.

Texture is also an essential visual feature in defining high- level semantics for image retrieval purposes. In [14], a novel, effective, and efficient characterization of wavelet sub bands by bit-plane extractions in texture image retrieval was presented. In order to overcome some limitations, such as computational ex- pensive approaches or poor retrieval accuracy, in a few texture- based image retrieval methods, Kokare *et al.* [15] concentrated on the problem of finding good texture features for CBIR. They designed 2-D rotated complex wavelet filters to efficiently handle texture images and formulate a new texture-retrieval algorithm using the proposed filters.

Liapis and Tziritas [17] explored image retrieval mechanisms based on a combination of texture and color features. Texture features are extracted using discrete wavelet frame analysis. Two- or one-dimensional histograms of the CIE Lab chromaticity coordinates are used as color features. Chun *et al.* [18] proposed a CBIR method based on an efficient combination of multi resolution color and texture features. As its color features, color auto correlograms of the hue and saturation component images in HSV color space are used. As its texture features, block difference of inverse probabilities and block variation of local correlation coefficient moments of the value component image are adopted. The color and texture features are extracted in multi resolution 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 IGA-based image retrieval system that uses wavelet coefficients to represent physical features of images. Cho [19] applied IGA to solve the problems of fashion design and 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. Arevalillo-Herráez *et al.* [11] introduced a new hybrid approach to relevance feedback CBIR. Their technique combines an IGA 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. Under the situation that the target is unknown, face image retrieval has particularity. Shi *et al.* [12] proposed an IGA-based approach which incorporates an adjust function and a support vector machine. Their method can prevent the optimal solution from losing, accelerate the convergence of IGA, and raise retrieval performance.

III. Image Features And Iga

One of the key issues in querying image databases by similarity is the choice of appropriate image descriptors and corresponding similarity measures. In this section, we first present a brief review of considered low-level visual features in our approach and then review the basic concept of the IGA.

A. Color Feature

A color image can be represented using three primary color spaces. Since the RGB space does not correspond to the human way of perceiving the colors and does not separate the luminance component from the chrominance ones, we used the HSV color space in our approach. HSV is an intuitive color space in the sense that each component contributes directly to visual perception, and it is common for image retrieval systems [11], [13]. Value refers to the perceived light intensity. The important advantages of HSV color space are as follows: good compatibility with human intuition, separability of chromatic and achromatic components, and possibility of preferring one component to other [14]. The color distribution of pixels in an image contains sufficient information. The mean of pixel colors states the principal color of the image, and the standard deviation of pixel colors can depict the variation of pixel colors. The variation degree of pixel colors in an image is called the color complexity of the image. We can use these two features to represent the global properties of an image. In addition to the global property of an image, the local color properties in an image play also an important role to improve the retrieval performance. Hence, a feature called binary bitmap can be used to capture the local color information of an image. The basic concept of binary bitmap comes from the block truncation coding [15], which is a relatively simple image coding technique and has been successfully employed in many image processing applications. There are three steps to generate the image binary bitmap. This method first divides an image into several non overlapping blocks.

B. Texture Feature

Texture is an important attribute that refers to innate surface properties of an object and their relationship to the surrounding environment. If we could choose appropriate texture descriptors, the performance of the CBIR should be improved. We use a gray level co-occurrence matrix (GLCM), which is a simple and effective method for representing texture [16].

C. Edge Feature

Edges in images constitute an important feature to represent their content. Human eyes are sensitive to edge features for image perception. One way of representing such an important edge feature is to use a histogram. An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image.

1) An image is divided into 4×4 sub images.
2) Each sub image is further partitioned into non overlapping image blocks with a small size.
3) The edges in each image block are categorized into five types: vertical, horizontal, $45°$ diagonal, $135°$ diagonal and non directional edges
4) Thus, the histogram for each sub image represents the relative frequency of occurrence of the five types of edges in the corresponding sub image.
5) After examining all image blocks in the sub image the five-bin values are normalized by the total number of blocks in the sub image. Finally, the normalized bin values are quantized for the bin values.

D. IGA

GAs [18], within the field of evolutionary computation, are robust, computational, and stochastic search procedures modeled on the mechanics of natural genetic systems. GAs are well known for their abilities by efficiently exploring the unexplored regions of the search space and exploiting the knowledge gained via search in the vicinity of known high- quality solutions. In general, a GA contains a fixed-size population of potential solutions over the search space. These potential solutions of the search space are encoded as binary or floating-point strings, called chromosomes. The initial population can be created randomly or based on the problem- specific knowledge. In each iteration, called a generation, a new population is created based on a preceding one through the following three steps: 1) evaluation—each chromosome of the old population is evaluated using a fitness function and given a value to denote its merit; 2) selection—chromosomes with better fitness are selected to generate the next population; and 3) Mating—genetic operators such as crossover and mutation are applied to the selected chromosomes to produce new ones for the next generation. The aforementioned three steps are iterated for many generations until a satisfactory solution is found or a termination criterion is met.

GAs have the following advantages over traditional search methods: 1) They directly work with a coding of the parameter set; 2) the search process is carried out from a population of potential solutions; 3) payoff information is used instead of derivatives or auxiliary knowledge; and 4) probabilistic transition rules are used instead of deterministic ones. Recently, since the computation abilities of computers have become enormously enhanced, GAs have been widely applied in many areas of engineering such as signal processing, system identification, and information mining problems [19]–[12]. In [13], GAs is applied to exercise difficulty-level adaptation in schools and universities with very satisfactory results.

IGA is a branch of evolutionary computation. 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. Through repeated rounds of content generation and fitness assignment, IGA enables unique content to evolve that suits the user's preferences. Based on this reason, IGA can be used to solve problems that are difficult or impossible to formulate a computational fitness function, for example, evolving images, music, various artistic designs, and forms to fit a user's aesthetic preferences.

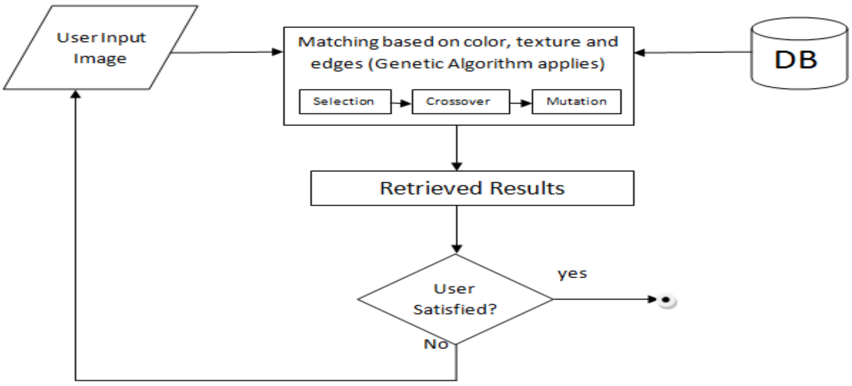

Fig. 1. Proposed System

IV. Proposed System

In general, an image retrieval system usually provides a user interface for communicating with the user. It collects the required information, including the query image, from the user and displays the retrieval results to him. However, as the images are matched based on low-level visual features, the target or the similar images may be far away from the query in the feature space, and they are not returned in the limited number of retrieved images of the first display. Therefore, in some retrieval systems, there is a relevance feedback from the user, where human and computer can interact to increase retrieval performance.
According to the aforementioned concept, we design a CBIR image retrieval system based on IGA, as shown in Fig. 1. Our system operates in four phases.

1) **Querying**: A sample image is given as a query for the system by the user.
2) **Matching Process**: The system computes the similarity between the query image and the database images according to the low-level visual features such as texture, color and edge.
3) **Retrieval**: The system retrieves and presents a sequence of images ranked based on priority. As a result, the image with higher priority will be displayed first.
4) **Incremental search**: After obtaining some relevant images, the system provides an interactive mechanism via IGA, which lets the user, evaluates the retrieved images as more or less relevant to the query one, and the system then updates the relevance information to include as many user-desired images as possible in the next retrieval result. The search process is repeated until the user is satisfied with the result or results cannot be further improved.

When we apply the IGA to develop a content-based color image retrieval system, we must consider the following components:

Solution representation: In order to apply GA to a given problem, one has to make a decision to find an appropriate genotype that the problem needs, i.e., the chromosome representation. In the proposed approach, a chromosome represents the considered three types of image features (i.e., color, texture, and edge) in an image.
Initial population: The IGA requires a population of potential solutions to be initialized at the beginning of the GA process. Usually, the initialization process varies with the applications; here, we adopt the first query results of a sample image as initial candidate images.
Fitness function: The fitness function is employed to evaluate the quality of the chromosomes in the population. The use of IGA allows the fusion of human and computer efforts for problem solving [5]. Since the objective of our system is to retrieve the images that are most satisfied to the users' need, the evaluation might simultaneously incorporate users' subjective evaluation and intrinsic characteristics of the images.
A user's preference is included in the fitness evaluated by the user. We use an impact factor to indicate the human's judgment or preferences, and the values of the impact factor are carried out with constant range from 0.0 to 1.0 with an interval of 0.1.

Genetic operators: The selection operator determines which chromosomes are chosen for mating and how many off spring that each selected chromosome produces. Here, we adopt the tournament selection method [10] because the time complexity of it is low. It does not require a global fitness comparison of all individuals in a population; therefore, it can accelerate the evolution process.

Fig. 2. Sample images of each category of the image database

The crossover operator randomly pairs chromosomes and swaps parts of their genetic information to produce new chromosomes. We use the one-point crossover [40] in the proposed approach. Parts of the two chromosomes selected based on fitness are swapped to generate trait-preserving off springs. The mutation operator creates a new chromosome in order to increase the variability of the population. However, in order to speed up the evaluation process, we do not consider the mutation operator.

V. Experimental Results

This CBIR technique is commonly used in on line shopping now-a-days. The proposed region-based method has been applied in the retrieval procedure and the experiments were performed. The below given figure is the sample database which contains the sample images. To show the effectiveness of the proposed system, some experiments will be reported. Selecting a suitable image database is a critical and important step in designing an image retrieval system. At the present time, there is not a standard image database for this purpose. Also, there is no agreement on the type and the number of images in the database. Since most image retrieval systems are intended for general databases, it is reasonable to include various semantic groups of images in the database.

A. Demonstration

At first, we give an example to illustrate our proposed system. A user submits an image containing a rose as the query image into the system, and then, the similarity measurement module of the system compares the query features with those images in the database and finds the most similar images to the query image. These images are ranked based on the similarity. After the user evaluates these images, the system adjusts the similarity measure according to the user's point of view and provides refined search results. The user can repeat this process until he/she is satisfied with the retrieval results.

(a)

(b)

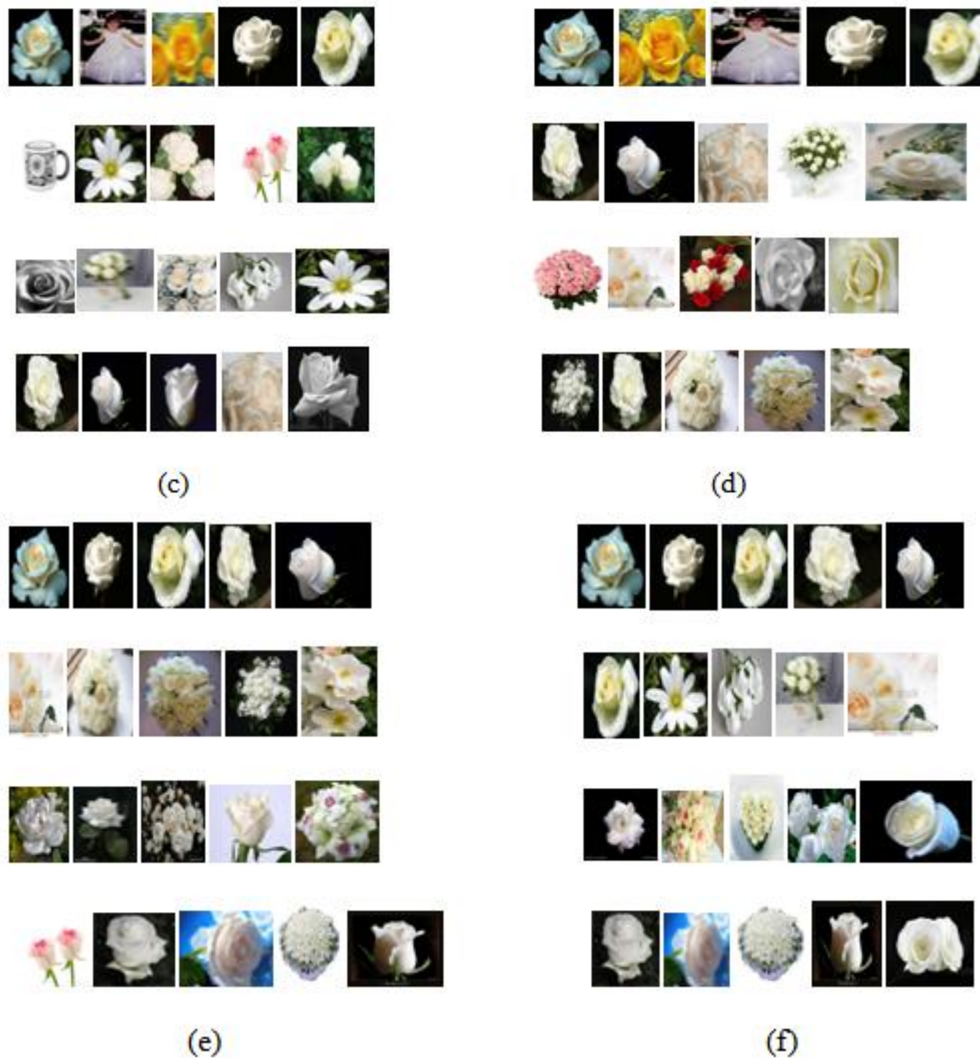

Fig. 3. Retrieval process. (a) Query image. (b) Retrieved results obtained by visual features similarity criterion. Retrieved results after (c) the first, (d) the second, (e) the third, and (f) the fourth generation of IGA.

In order to verify the influence of the mutation operator, we employed it into our approach and evaluated its performance. The conditions and procedures of this experiment are the same as the previous one, and we used the precision as the performance measure. Fig. 6 shows the retrieval results. It is clear that the use of a mutation operator needs more generations to achieve good results. Meanwhile, it does not provide significant improvement in the retrieval performance. The phenomenon results from that the mutation operator may be likely to disrupt good chromosomes (i.e., user's preferred images) rather than improve them.

VI. Conclusion

This project presents an effective framework for content based product image retrieval with promising result. A fast and efficient approach to extract the image is proposed and Image Feature is used to extract the image. The search process is carried out from a population of potential solutions; the test image is chosen from the database by the input texture given by the user. In general, an image retrieval system usually provides a user interface for communicating with the user. It collects the required information, including the query image, from the user and displays the retrieval results to him. In addition, the entropy based on the GLCM and edge histogram is considered as texture descriptors to help characterize the images. In particular, the IGA can be considered and used as a semi automated exploration tool with the help of a user that can navigate a complex universe of images. Experimental results of the proposed approach have shown the significant improvement in retrieval performance. Further work considering more low-level image descriptors or high-level semantics in the proposed approach is in progress.

VII. Future Enhancement

In this work, we study the use of Genetic algorithm and Image feature method to retrieve the image from the database. Genetic algorithm is a promising type of algorithm technique for retrieving images where comparison of images is used to retrieve. Further research plans include optimization of global and category parameters as well as integrating image as input for retrieval procedure.

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International Journal of Engineering Science Invention (IJESI) is UGC approved Journal with Sl. No. 3822, Journal no. 43302.

G.Barani "Content Based Image Retrieval Based On Internal Regions Using Clustering Methods in Interactive Genetic Algorithm" International Journal of Engineering Science Invention (IJESI), vol. 07, no. 02, 2018, pp. 32–38.