RETRIEVAL OF IMAGES BASED ON LOW LEVEL FEATURES USING GENETIC ALGORITHM

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ABSTRACT

Content-based image retrieval is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. In content-based image retrieval (CBIR), image content is frequently represented through image features. Commonly used features include color, texture, or shape descriptors for objects found within an image. This paper proposes an image retrieval method based on multi-feature similarity score fusion using genetic algorithm. Here the image retrieval is based on color feature, texture feature and shape feature using Zernike moments. Finally genetic algorithm is used for optimization process.

Keywords: CBIR, Genetic Algorithm, Spatial, Texture Analysis

I. INTRODUCTION

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 [1]. However, there remain many challenging research problems that continue to attract researchers from multiple disciplines.

A. OBJECTIVE OF THE THESIS

The primary goal our project is to reduce the computation time and user interaction. The conventional Content Based Image Retrieval (CBIR) systems [2] also display the large amount of results at the end of the process this will drove the user to spend more time to analyze the output images. In our proposed system we compute texture feature and color feature for compute the similarity between query and database images. [5] GLCM and CCM techniques are used to extract the color and texture feature of the image. Finally genetic algorithm is applied for optimization process.

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B. SYSTEM ARCHITECTURE

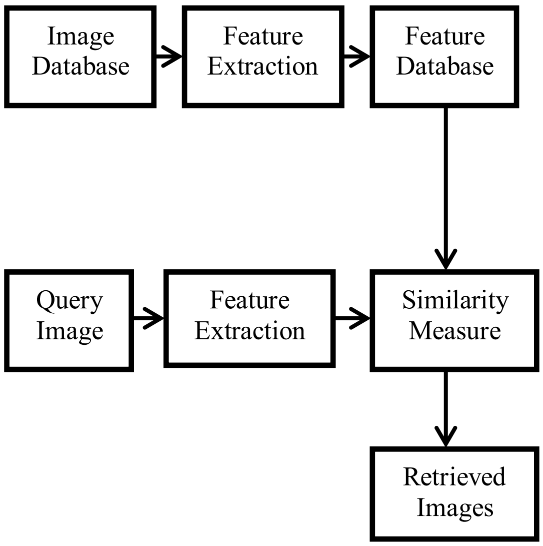

Figure I.a Common Architecture

II. IMPLEMENTATION

A. IMAGE FEATURE EXTRACTION

The image content is mainly embodied in color, texture and shape etc. The color feature, texture feature and shape feature describe the image content from different angle. More features will provide more information on the image content. This paper focuses on fusion method of multi feature similarity score. For convenience, this paper only discusses the fusion method of two-feature similarity score.

B. COLOR FEATURE EXTRACTION

Hue, Saturation, Value or HSV is a color model that describes colors (hue or tint) in terms of their shade (saturation or amount of gray) and their brightness (value or luminance). The HSV color wheel may be depicted as a cone or cylinder. Instead of Value, the color model may use Brightness, making it HSB (Photoshop uses HSB) [3]. Hue is expressed as a number from 0 to 360 degrees representing hues of red (starts at 0), yellow (starts at 60), green (starts at 120), cyan (starts at 180), blue (starts at 240), and magenta (starts at 300). Saturation is the amount of gray (0% to 100%) in the color. Value (or Brightness) works in conjunction with saturation and describes the brightness or intensity of the color from 0% to 100%.

C. TEXTURE FEATURE EXTRACTION USING GLCM

The Gray Level Co-occurrence Matrix1 (GLCM) and associated texture feature calculations are image analysis techniques [4]. Given an image composed of pixels each with an intensity (a specific gray level), the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use

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the contents of the GLCM to give a measure of the variation in intensity (a.k.a. image texture) at the pixel of interest [6]. Echo view offers a GLCM texture feature operator that produces a virtual variable which represents a specified texture calculation on a single beam echogram.

The virtual variable is created in the following way:

1. Quantize the image data. Each sample on the echogram is treated as a single image pixel and the value of the sample is the intensity of that pixel. These intensities are then further quantized into a specified number of discrete gray levels as specified under **Quantization**.

2. Create the GLCM. It will be a square matrix N x N in size where N is the **Number of levels** specified under **Quantization**. The matrix is created as follows:

   a. Let s be the sample under consideration for the calculation.
   b. Let W be the set of samples surrounding sample s which fall within a window centered upon sample s of the size specified under **Window Size**.
   c. Considering only the samples in the set W, define each element i,j of the GLCM as the number of times two samples of intensities i and j occur in specified **Spatial relationship** (where i and j are intensities between 0 and **Number of levels**-1) .

The sum of all the elements i, j of the GLCM will be the total number of times the specified spatial relationship occurs in W.

4. Make the GLCM symmetric:

   1. Make a transposed copy of the GLCM.

   2. Add this copy to the GLCM itself.

This produces a symmetric matrix in which the relationship i to j is indistinguishable for the relationship j to i (for any two intensities i and j) [8]. As a consequence the sum of all the elements i, j of the GLCM will now be twice the total number of times the specified spatial relationship occurs in W, and for any given i, the sum of all the elements i, j with the given i will be the total number of times a sample of intensity i appears in the specified spatial relationship with another sample.

5. Normalize the GLCM:

   1. Divide each element by the sum of all elements

   2. The elements of the GLCM may

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now be considered probabilities of finding the relationship i, j (or j, i) in W.

3. Calculate the selected Feature. This calculation uses only the values in the GLCM [8]. The sample s in the resulting virtual variable is replaced by the value of this calculated feature.

D. FEATURE EXTRACTION BASED ON CCM

Assuming color image is divided into *N* * *N* image sub blocks, for anyone image sub-block T(i, j) ($1 \le i \le N, 1 \le j \le N$) , using the main color image extraction algorithm [9] to calculate the main color C(i, j) . For any two 4-connected image sub-block T(i, j) and T(k ,l) (i − k =1 and j = 1 ; or j − l = 1 and i = k) , if its corresponds to the main color and in the HSV space to meet the following condition. a. Cj And Ci belong to the same color of magnitude, that is, its HSV Components hi = hj , si = s j , vi = v j ; b. Cj And Ci don't belong to the same color of magnitude, but satisfy si∗3 + vi = s j ∗3 + v j , and hi − hj = 1; or satisfy hi = hj , si = s j and vi , v j ∈{0,1} . We can say image sub-block T(i, j) and T(k ,l) are color connected. According to the concept of color-connected regions, we can make each sub-block of the entire image into a unique color of connected set S = {Ri}($1 \le i \le M$) in accordance with guidelines 4-connected The set *S* corresponds to the color-connected region. The statistic features extracted from CCM are as follows.

$$\text{Energy } E = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} m(i,j)^2 \qquad (1)$$

$$\text{Contrast } C = \frac{1}{(G-1)^2}\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} (i-j)^2\, p(i,j) \qquad (2)$$

$$\text{Entropy } S = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} m(i,j)\log m(i,j) \qquad (3)$$

E. SHAPE FEATURE EXTRACTED USING ZERNIKE MOMENTS

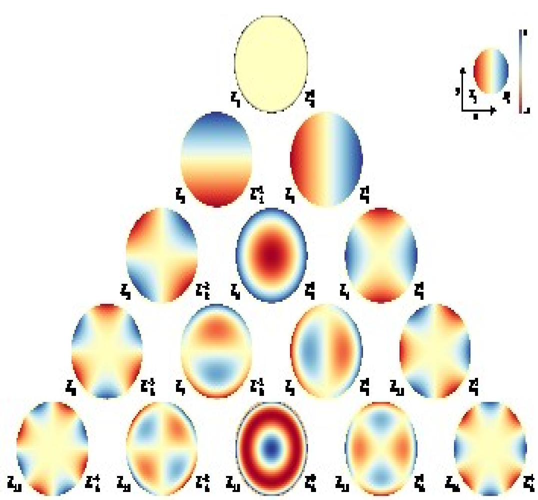

Figure II.a

In mathematics, the Zernike polynomials are a sequence of polynomials that are orthogonal on the unit disk. There are even

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and odd Zernike polynomials [7]. The even ones are defined as

$$Z_n^m(\rho,\varphi) = R_n^m(\rho)\,\cos(m\,\varphi)$$

and the odd ones as

$$Z_n^{-m}(\rho,\varphi) = R_n^m(\rho)\,\sin(m\,\varphi),$$

Where m and n are nonnegative integers with n≥m, φ is the azimuthalangle, and ρ is the radial distance $0 \le \rho \le 1$. Zernike polynomials have the property of being limited to a range of -1 to +1, i.e. $|Z_n^m(\rho,\varphi)| \le 1$. The radial polynomials R^m_n are defined as

$$R_n^m(\rho) = \sum_{k=0}^{(n-m)/2} \frac{(-1)^k\,(n-k)!}{k!\,((n+m)/2-k)!\,((n-m)/2-k)!}\;\rho^{n-2k}$$

For n − m even, and are identically 0 for n − m odd.

F. FUSION USING ADVANCED GENETIC ALGORITHM

A genetic algorithm (GA) is a search heuristic that mimics the process of natural selection. This heuristic (also sometimes called a meta heuristic) is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.

In a genetic algorithm, a population of candidate solutions to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a generation. In each generation, the fitness of every individual in the population is evaluated; the fitness is usually the value of the objective function in the optimization problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

A typical genetic algorithm requires:

1. a genetic representation of the solution domain,

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2. a fitness function to evaluate the solution domain.

III. RESULTS

TRAINING PHASE

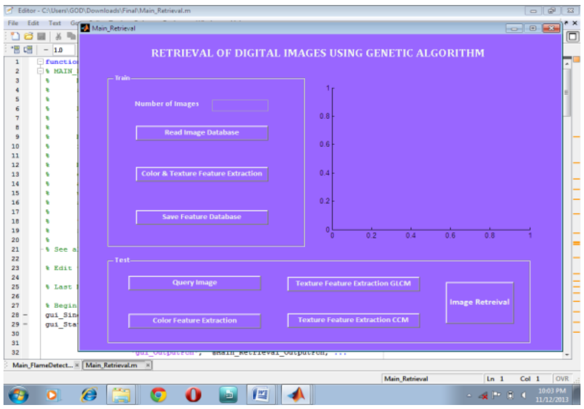

Figure III.a

READING OF IMAGES

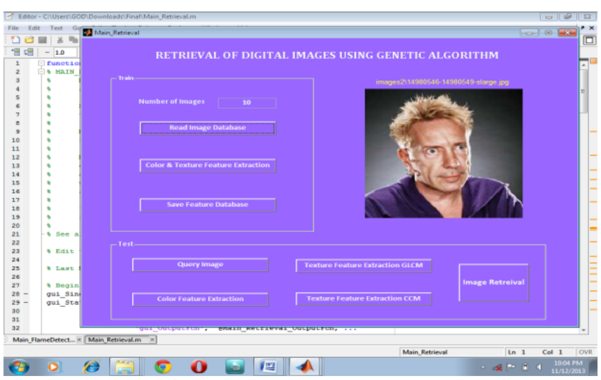

Figure III.b

COLOR AND TEXTURE FEATURE EXTRACTION

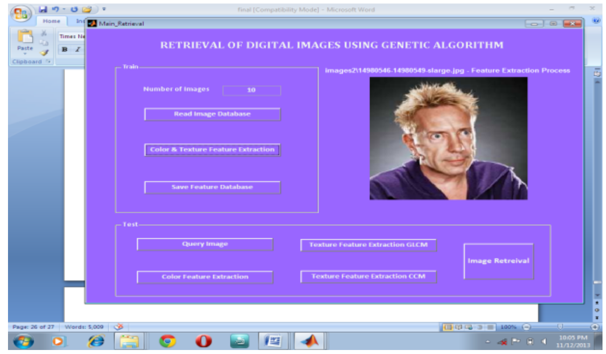

Figure III.c

SAVE THE EXTRACTED FEATURES

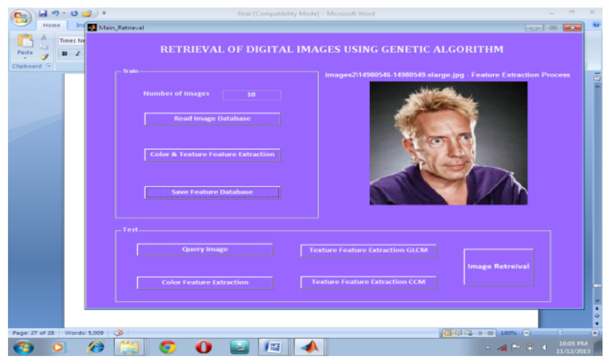

Figure III.d

QUERY IMAGE

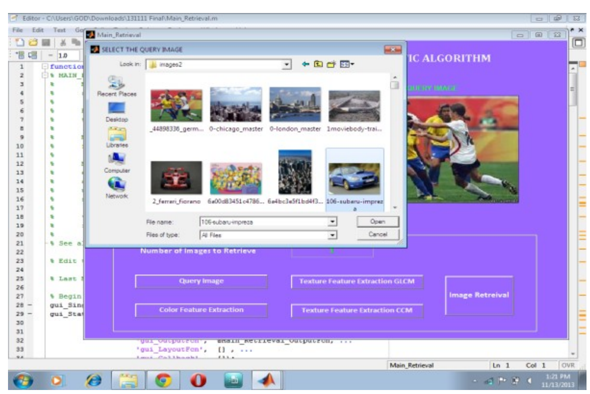

Figure III.e

COLOR AND TEXTURE FEATURE EXTRACTION FOR QUERY IMAGE USING GLCM AND CCM

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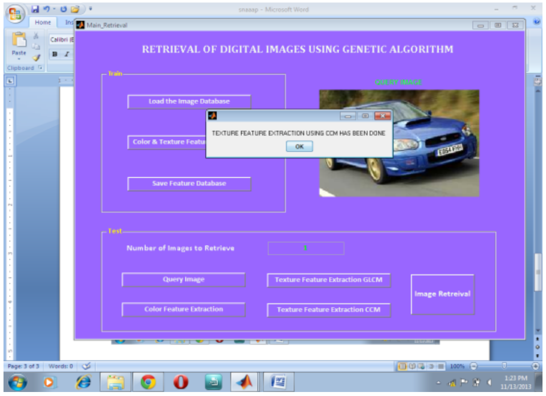

Figure III.f

QUERY IMAGE RETRIEVAL

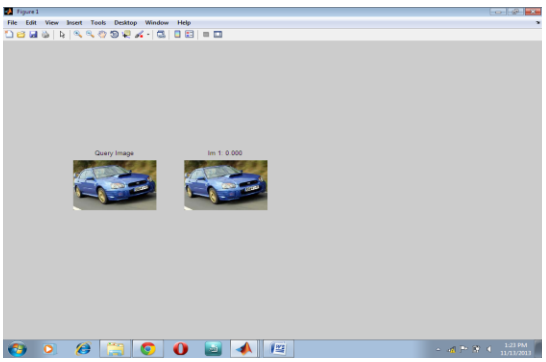

Figure III.g

IV. CONCLUSION

This thesis proposed an image retrieval method based multi-feature similarity score fusion. For a query image, multiple similarity score lists based on different features are obtained. Then using genetic algorithm, multi-feature similarity scores are fused, and better image retrieval results are gained. In this paper, when we evaluated the fitness of an individual, we considered only the occurrence frequencies of an image in retrieval result, and not the location of an image in retrieval result. However, the location of an image in retrieval result reflects directly the similarity of it and query image. So, this factor should be taken into account when evaluating the fitness of an individual, which is also our future work. The process of feature extraction has been completed up to the phase 1 part. The first process in our approach is that the feature extraction part. There are two features extracted such as color and textures. The next part will be the fusion of these two features and perform retrieval of images using genetic algorithm.

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