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Comparison of Optimized Image Retrieval Methods Based on Color and Texture Features

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Abstract: Nowadays our lives intensively depend upon multimedia based information acquired from different sources such as internet, television, radio, cellular phones etc. These multimedia documents were retrieved using their associated text contents. However, a significant amount of non-textual data is also available on these documents that may be omitted due to inappropriate keywords. There are various examples where text based query is highly inefficient. To resolve this issue there is a lot of research being done on Contents Based Image Retrieval (CBIR). However, it is identified that optimization for CBIR methods was an unattended issue. Moreover, a comprehensive comparison of such optimization methods is not available for researchers who want to attack this issue.

In this paper a comparative study of various optimization methods for CBIR is presented. Particularly, Similarity Index Measure (SIM), Genetic Algorithm (GA) and Interactive GA (IGA) are under consideration

***Index Terms*—Colour Based Image Retrieval, Genetic algorithm, interactive genetic algorithm**

1. INTRODUCTION

Previously majority of information was primarily text based. But with the rapid growth in the field of computer networks and low cost permanent storage media, the shape of information has become more interactive. People are accessing more multimedia files than the past such as (Smeulders *et al.,* 2000), (Goodrum, 2000); (Datta *et al.,* 2008), (Liu *et al.,* 2007); (Lew *et al.,* 2006), and (Rui, Huang and Chang, 1999). In past image, video and audio files were only used for entertainment purpose but nowadays these are a major source of information. Because of intense dependency on multimedia files contents based retrieval is a major problem as the search engine searches text associated with the multimedia files, instead of their contents. Intelligent and optimized text searching has already matured but there is a gigantic space available for the intelligent and optimized CBIR.

CBIR is a method that helps in searching user desired information from a huge set of image files and interprets user intentions for the information. The retrieval of information is function of visual descriptors of an image such as color, shape, and texture etc.

(a) Research Challenge

In this age of information technology we intensively depend on visual information and its contents. This creates an urgent need to device new methods to archive and retrieve multimedia documents. Conventional databases only retrieve images based on the keyword associated with it. (Veltkamp and Tanase, 2002) highlight applications like Biomedical, Digital libraries, multimedia archives, geographical information systems (GIS), and academics which are surrounded by rich and un-optimized text description that may provide just contextual hints or semantic information about the contents. The optimization cannot be achieved with this rich text description because most of the text is not relevant with the contents information. Moreover, this approach is highly infeasible even for a slightly large dataset, because of two main reasons. Firstly, it is extremely time and labour expensive. Secondly, image labelling is often subjected to individual user perceptions.

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Most of the existing method use associated text to retrieve images. This approach fails to mimic user intentions as evident from (Krishnapuram *et al.,* 2004). Regardless of the progression in CBIR, different areas need research attention. The main problems is the optimize image retrieval and semantic interpretation of the image content. Therefore, to design optimized CBIR is a research challenge.

Some researchers have proposed some methods in this regard as mentioned in Section III. Each one of these methods looks good in isolation. However, a comprehensive performance comparison is not available. This performance comparison is indeed needed in order for other researcher to modify one of these methods and design a new method.

Different approaches are also available at prototype level such as: IBM 's QBIC in (Hafner *et al.,* 1995), SIMPLIcity in (Wang, Li and Wiederhold, 2001), blob world in (Carson *et al.,* 1997), VisualSeek (Smith and Chang, 1997), MARS (Porkaew, Ortega and Mehrota, 1999) etc.

(b) Literature Review

The evolution of contents based image retrieval started from late 1970s. Till early 2000 majority of work focused on improving the quality of image retrieval and the perceptive user intentions.

Like (Pass and Zabih, 1996) used histogram refinement for image retrieval. Specifically they used color coherent vector (CCV) as a local descriptor. A similarity is function of distance between query image's CCV and CCV table for database. Retrieved images are indexed according to their similarity.

(Carson *et al.,* 1997) used combine color and texture feature vector. Each image in a database has been transform into a corresponding feature vector. This approach is insufficient to handle the semantic gap issue.

(Rui, Huang and Mehrotra, 1997) proposed image retrieval method using relevance feedback. This approach is specifically focus on reducing semantic gap. Although this approach greatly reduces human effort but at the cost of high computation time.

(Berretti, Bimbo and Pala, 2000) used shape as a local descriptor. They proposed to segment image and find the shape feature for corresponding segmented region.

(Vertan and Boujemaa, 2000) identified fuzziness of color in histogram type descriptors. They embedded fuzzy logic system (FLS) in CBIR but the experimental results showed that the average precision of result was just about 57% to 58 % which is insufficient for major applications.

(Chen and Wang, 2001) proposed a soft computing approach, which greatly increased the robustness of the retrieval system against segmentation related uncertainties. This approach computes similarity based on fuzzified regions of corresponding image.

(Han and Ma, 2002) proposed novel approach for image retrieval that is called fuzzy color histogram (FCH). This approach is based on color similarity of each pixel's color associated to all the histogram bins through fuzzy-set membership function. This approach is further employed in image indexing and retrieval.

(Banerjee and Kundu, 2003) used fuzzy compactness and shape information a visual descriptor for edge map. This approach do not required image segmentation for indexing. This approach was proved to be computationally less expensive as compared to other related approaches. In this model, the optimization of image and machine learning for new images was remain unattended.

(Wang *et al.,* 2004) use fuzzy K-NN classification for autonomous metadata generation for corresponding image document. Preliminary experimental results were very encouraging. However, still this approach is insufficient to handle the semantic gap.

(Krishnapuram *et al.*, 2004) present fuzzy set theory based image retrieval called FIRST (Fuzzy Image Retrieval SysTem). But the system is limited to the defined set of images. It did not have adaptive features and significance of optimization was still unattended.

It can be infer from the literature review that researcher are focused on devising efficient visual image descriptors and classification method. However, less attention has been payed toward the optimization issue of retrieval system.

I. EXPERIMENTAL SETUP

Following are elements of experimental setup, which includes visual features extraction and application of optimization techniques for image retrieval.

(a) The Color Feature

Color is the most commonly used and dominant descriptor. This is because color descriptors are illumination, view angle, size and scale invariant. There are numerous methods employed in image retrieval using color descriptors. In the proposed approach measure of central tendency and measure of dispersion is used as visual descriptor. As shown in Equation 2 and Equation 3:

$$Pi = \begin{bmatrix} Ri \\ Gi \\ Bi \end{bmatrix} \tag{1}$$

$$\mu = \frac{1}{M}\sum_{i=1}^{M} Pi \tag{2}$$

$$\sigma = \left[\frac{1}{M-1}\sum_{i=1}^{M}(Pi-\mu)^2 \right]^{1/2} \tag{3}$$

(b) The Texture Feature

The texture descriptor represents the measure of smoothness, coarseness, and regularity of an image document. It helps in extracting the perceptual similarity of image. In proposed approach, the entropy is computed to represents texture descriptor. This can be commutated using Equation 4.

$$Entropy(E) = -\sum_i \sum_j C(i,j)\log C(i,j) \tag{4}$$

(c) Feature Vector

In proposed approach first of all feature vector is constructed containing mean, standard deviation of RGB color feature and entropy of image as texture feature. Feature vector is shown in Equation 5.

$$FV = \left\lfloor \mu_r \mu_g \mu_b \sigma_r \sigma_g \sigma_b E \right\rfloor \tag{5}$$

Each image in a database has a corresponding feature vector that serves as an image descriptor. All feature vectors are recorded in Feature Vector Table (FVT). FVT table has the ability to evolve for new input images.

(d) Image Retrieval Using SIM

In similarity measure technique for image retrieval we first convert all database images into their corresponding feature vectors consisting of normalized mean and standard deviation of RGB color and normalized entropy of image. Each image in a database corresponds to a feature vector and stored in feature vector table. The query image is first converted into its corresponding feature vector. Using similarity index method, we first take difference of each feature of the input image with that of each image in the database. For each image, the all differences are added and called the cumulative difference of the given image to that image in the database. The image in the database with which the cumulative difference is the least is supposed to be the best match with the input image. We have a dataset of 360 images with four classes, i.e., Bus, Flower, Horse and Landscape respectively.

(e) Image Retrieval Using Genetic Algorithm

We also use GA to retrieve image on the basis of the optimal difference between color and texture features. Initially we use random population and compute fitness of each individual on the basis of the fitness function shown in Equation 6.

$$d.(q,c) = \sqrt{\sum_{(R,G,B)}(\mu_i^{'q} - \mu_i^{'c})^2 + \sum_{(R,G,B)}(\sigma_i^{'q} - \sigma_i^{'c})^2} + \left|E^q - E^c\right| \tag{6}$$

Where, μ, σ, and E are normalized mean value, standard deviation, and the entropy of the image respectively.

(f) Image Retrieval Using Interactive Genetic Algorithm (IGA)

In IGA the initial population is generated from input image feature vector. Initial population size and all other parameters like (generations, cost function, cross over method and mutation bits). However, we generate defined value set of population instead of random population and then we apply the fitness function as given in Equation 6.

II. Simulation results & Discussions

In this paper we compare retrieval efficiency and computational cost of different methods for Image Retrieval (IR) based on color and texture features.

We take 360 images as input sample with four classes as shown in Table 1. We use Matlab as a simulation tool with customized code instead of embedded toolbox of MatLab.

Table 1. Input Class

Image Category	Class	Image
BUS	A	001.JPG to 090.JPG
FLOWER	B	091.JPG to 180.JPG
HORSE	C	181.JPG to 270.JPG
LANDSCAPE	B	270.JPG to 360.JPG

Following are the experimental results. We take image from each class as a query image and plot its cost corresponding to each image. Cost actually represents the difference between both query image and image stored in database as shown in Figure 1(a) – 1(d).

Figure 1(a), 1(b), 1(c), and 1(d) show cost when the query image is from Class A, B, C, and D respectively. Each figure gives cost using three different methods, i.e., SIM, GA, IGA in red, green, and blue respectively. We can see from Figure 1(a) that for each query image in class A, SIM cost is very low for class A and relatively high for the other classes. Similar response can be seen for GA and IGA in the same figure. More or less same pattern of results for image as query from class B, C and D is visible in Figure 1(b), (c), and 1(d) respectively.

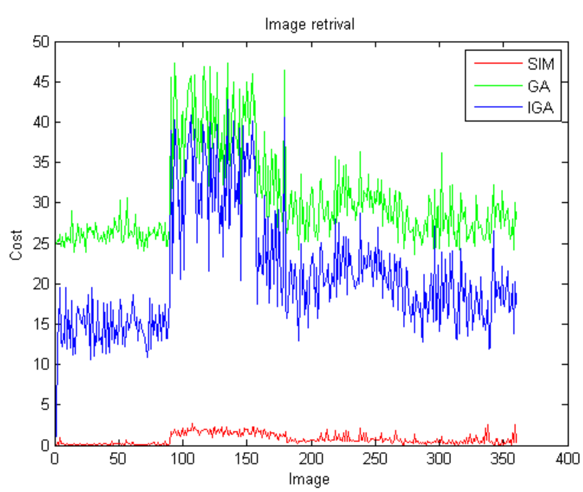

Figure 1(a): Class A image as query image

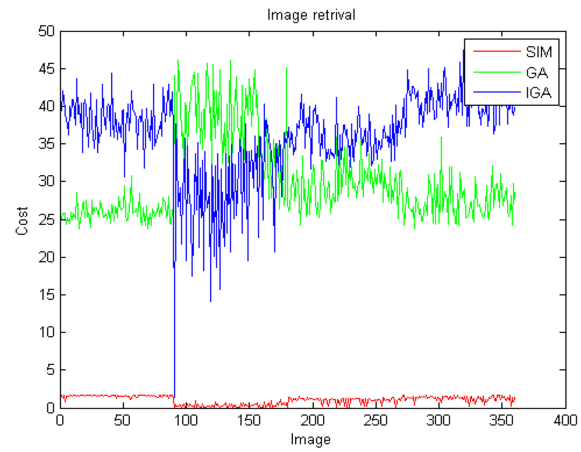

Figure 1(b) Class B image as query image

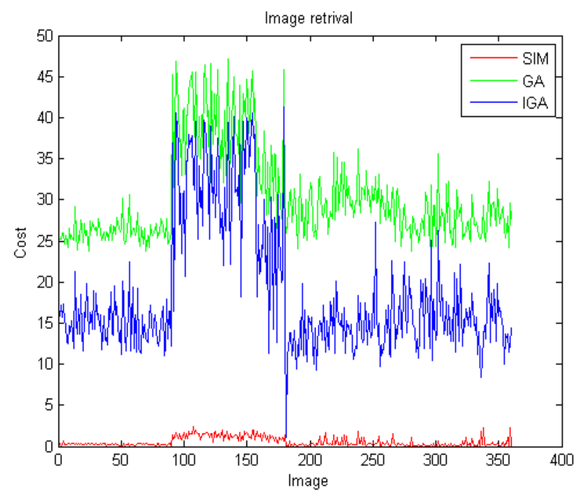

Figure 1(c) Class C image as query image

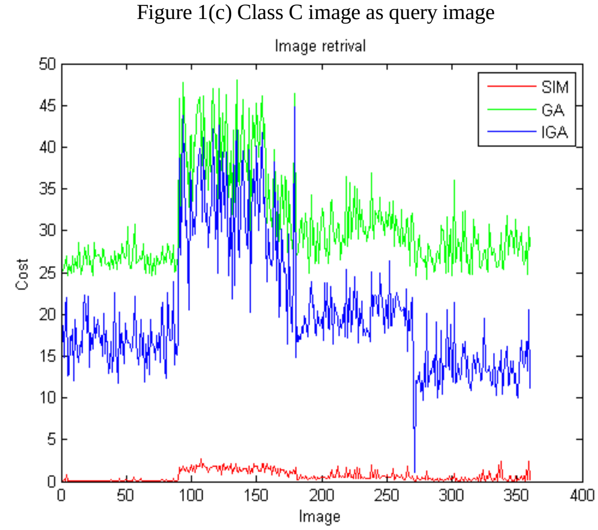

Figure 1(d) Class D image as query image

We come to the conclusion that it is difficult to classify images using SIM because cost difference between the class of the query image and other classes is not significant. On the other hand GA and IGA perform well because they produce significant difference of cost between images from query class to the other classes.

Figure 2 shows the computational cost as a function of time. Experimental results show that time as a cost is almost constant for each iteration and for each method with little deviation. Although computational cost of SIM is significantly low as compared to GA and IGA, but SIM is not useful in classification of images. On the other hand GA is good at classification but its computational cost is very high as evident from its curve in Figure 2. IGA is the only method which provides good classification (shown in Figure 1(a) – 1(d). as well as has a very low computational cost (blue curve in Figure 2).

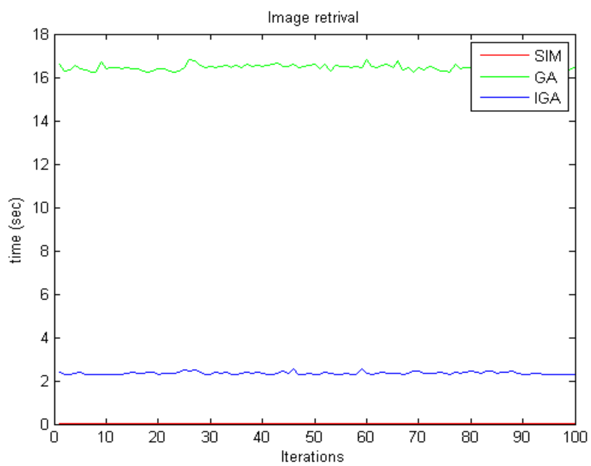

Figure 2 Computation cost of each iteration

Same behaviour is observable in Figure 3. The total computational time is very large for GA and considerably small for IGA. So we can claim that for image retrieval, IGA performs much better and very fast from conventional GA.

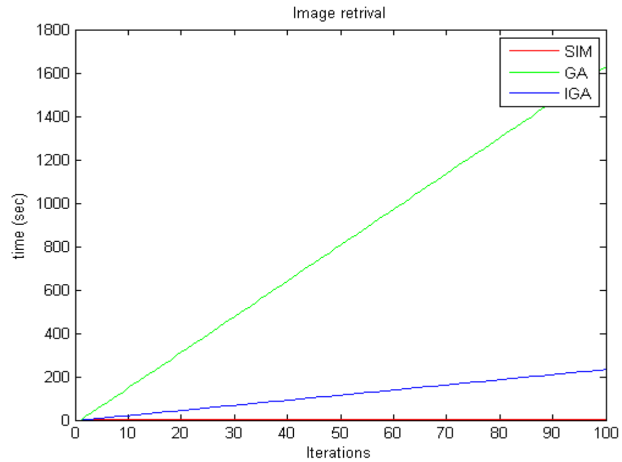

Figure 3 Total Computational cost

Figure 4 shows the retrieval probability for each method. It can be seen in this figure that for each class IGA has more consistent probability as compared to GA and SIM.

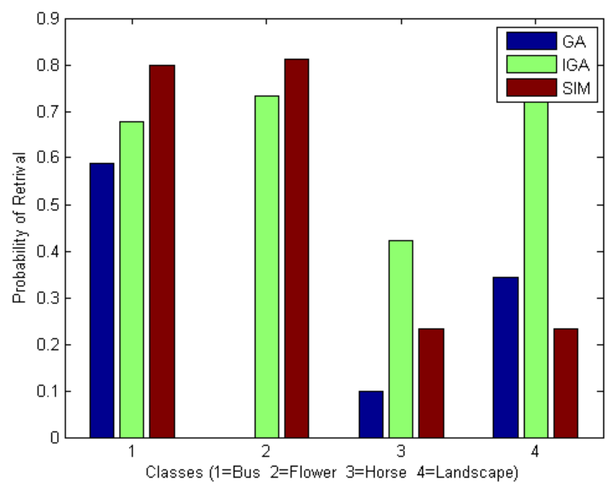

Figure 4 Probability of retrieval for each class

III. *CONCLUSION AND FUTURE DIRECTIONS

It is concluded that SIM method is computationally less demanding but probability of retrieving the image for different classes may vary and may be highly nonlinear in nature. GA can be used for retrieving the image but with the initial random population, the probability of retrieving desired image is low and computational cost is very high. However, results show that IGA is much faster than GA and desired image can be retrieved in less number of generations with higher retrieval probability.

As a future direction first it is suggested that different variant of evolutionary algorithm like (Particle swarm, Ant colony , Bees algorithm etc. can be applied to for optimize image retrieval, Second using evolutionary algorithm semantic gap between low level features and high level semantic can be reduce. Third approach can be tested on large data set.

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