

# Image Retrieval using Genetic Algorithm based on Multi-Feature Similarity Score Fusion

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**Abstract**— This paper proposes an image retrieval method based on multi-feature similarity score fusion using genetic Algorithm. Single feature describes image content only from one point of view and Fusing Multifeature similarity score is expected to improve the system's retrieval performance. In this paper, the retrieval results from color feature and texture feature are analyzed, and the method of fusing multi-feature similarity score is described. The main purpose of fusion weights of multi-feature similarity scores reasonably, then we will apply genetic algorithm. We will use other three methods are color feature, texture feature and fusion of color-texture feature similarity score with equal weights base on image retrieval. The implementation results show that the proposed method is superior to other methods.

**Key words:** image retrieval; fusion; genetic algorithm

## I. INTRODUCTION

As per the fast development of the internet technology now it's very easy to take up the multimedia information. First of all the user should know that from where the required multimedia information has to be collected. The most easiest and reliable source would be text query. Individual difference and state of human and environment, and the described results may be more one-sided. In addition, it is clearly incomplete to describe content-rich multimedia information with a small amount of text. Content Based Image Retrieval (CBIR) techniques appeared in 1990s [1]. It solves the above problems well. It uses low-level features like color, texture and shape to describe image content, and breaks through the limitation of traditional text query technique. Order to solve this issue this – Content Based Image Retrieval (CBIR), way was launched. It was a great breakthrough as it resolved the issues like color, texture & shape In etc to describe image content. In one way this helped to solve the issue of limitation in text query technique. An image from a specific angle. It may be suitable for some images, but it also may be difficult to describe other images. Moreover, describing an image with single feature is also incomplete. Representing an image with multi-features from multi-angles are expected to achieve better results. Information is multisource, and information fusion approach is diverse. The problem how to organize multi-source information in a suitable way to achieve the intended results attracts extensive attention from the researchers in this field.

Information fusion can be carried out in feature level [2]. Information fusion in feature level has advantage in some extent. Because different features reflect the different characteristics of the image, if those features are integrated reasonably, the results will both reserve the discriminate information of multi-feature and eliminate the interference resulted from the difference of multi-feature. B.G. Prasad et al. [3] proposed a technique to retrieve images by region matching using a combined feature index based on color, shape, and location within the framework of

MPEG-7. Dominant regions within each image are indexed using integrated color, shape, and location features. Young Deok Chun et al. [4] proposed content-based image retrieval method based on an efficient combination of multiresolution color and texture features. Color autocorrelograms of the hue and saturation component images in HSV color space are taken as color features. BDIP and BVLC moments of the value component image are adopted as texture features. The color and texture features are extracted in multiresolution wavelet domain and combined. Tai X. Y. et al. [5] defined a new image feature called color-texture correlogram which is the extension of color correlogram. The texture feature extracted by texture spectrum algorithm is combined with color feature vector, and then calculate the spatial correlation of color-texture feature vector. Hui Yu et al. [6] adopted local Fourier transform as a texture representation scheme and derive eight characteristic maps for describing different aspects of co-occurrence relations of image pixels in each channel of color space. Then they calculate the first and second moments of these maps as a representation of the natural color image pixel distribution, resulting in a 48-dimensional feature vector. The novel low-level feature is named color texture moments (CTM), which can also be regarded as a certain extension to color moments in eight aspects through eight orthogonal templates.

Information fusion can also be carried out in decision making level. Image retrievals based on different features are accomplished respectively, and then similarity score came from these results are fused according to some rules, a better result will be returned. Anil K. Jain et al. [7] integrated the results of the shape-based retrieval and the color-based retrieval by combining the associated similarity values with appropriate weights. Xiuqi Li et al. [8] proposed a novel approach to image retrieval using color, texture and spatial information. Color homogram filter, wavelet texture filter, and spatial filter are used in sequence to eliminate images that are dissimilar to a query image in color, texture, and spatial information from the search ranges respectively. The final query ranking is based on the total normalized distance in color, texture, and spatial information of all images passing the three filters. Ilya Markov et al. [9] proposed a technique to combine image similarity measures which takes into account a particular query-image. They introduced mixed-metrics obtained from color and texture metrics by using their weighted linear combination. Mladen Jovic et al. [10] proposed an image similarity method based on the fusion of similarity scores of feature similarity ranking lists. It takes an advantage of combining the similarity value scores of all feature types representing the image content by means of different integration algorithms when computing the image similarity.

This paper proposes an image retrieval method based on multi-feature similarity score fusion using genetic algorithm. This paper analyzed image retrieval results based on color feature and texture feature, and proposed a strategy

to fuse multi-feature similarity score. Further, with genetic algorithm, the weights of similarity score are assigned automatically, and a fine image retrieval result is gained. The rest of this paper is organized as follows. Section II describes the extraction method of color feature and texture feature. Section III introduced the strategy to fuse multifeature similarity score. The method assigning weights of multi-feature similarity score by genetic algorithm is given in section IV. Experimental results and analysis are in section V and section VI concluded the whole paper.

## II. IMAGE FEATURE EXTRACTION

The image content is mainly embodied in color, texture and shape etc. The color feature, texture feature and shape feature describes the image content from different angle. More features will provide more information on the image content. This paper focuses on fusion method of multifeature similarity score. For convenience, this paper only discusses the fusion method of two-feature similarity score. Without loss of generality, the used features are color feature and texture feature. The following part describes the used extraction method of color feature and texture feature.

### A. Color feature extraction

HSV color model forms a uniform color space, which uses a linear gauge. The perceived distance between colors is in proportion to Euclidean distance between corresponding pixels in HSV color model, and conforms to eye's feeling about color. So it is very suitable for color based image similarity comparison. In this paper, the color histogram in HSV color space is taken as the color feature describing image content. For calculating color histogram in HSV color space, HSV color space must first be quantified. According to human cognitive about color, three components of HSV space are quantified in non-uniform manner. Hue is quantized into 16 bins and is among [0, 15]. Saturation is quantized into 4 bins and is among [0, 3]. Value is quantized into 4 bins and is among [0, 3]. Among those three components, human cognitive about color is mainly based on hue, and then saturation, finally value. So, quantized results are coded as

$$C = 16H + 4S + V \quad (1)$$

Where  $C$  is an integer between 0 and 255 Thus the color feature can be obtained by calculating histogram of an image in HSV space.

### B. Texture feature extraction

In this paper, the statistical properties of image co-occurrence matrix are taken as texture features of an image. Firstly, color image is converted to grayscale image, and the image co-occurrence matrix is gained. Then, the following four statistical properties are calculated to describing image content. They are contrast, energy, correlation and Homogeneity. All these statistical properties are calculated in 4 directions, so we can get 16 texture features. At last, we calculated the means and variances of these four kinds of statistical properties, and took the results as the ultimate texture features, denoted as

$$T = (\mu_1, \mu_2, \mu_3, \mu_4, \mu_5; \sigma_1, \sigma_2, \sigma_3, \sigma_4, \sigma_5) \quad (2)$$

## III. MULTI-FEATURE SIMILARITY SCORE FUSION

Since the physical meanings of different features are different, and value ranges are totally different, similarity scores of different features cannot be compared. So, before multi-feature similarity score are fused, they should be normalized. Similarity scores can be normalized through the following ways. Let  $Q$  be the query image. By calculating distances between the query image and images in database, similarity score set  $\{S_i\}$  can be gotten, where  $i = 1, \dots, N$ ,

$N$  is the number of images in database. Thus, similarity score normalization can be implemented as

$$S_{Ni} = (S_i - \min\{S_i\}) / (\max\{S_i\} - \min\{S_i\}) \quad (3)$$

The results of multi-feature similarity scores is

$$S_{Fi} = (S_{NCi} \cdot W_c + S_{NTi} \cdot W_T) / (W_c + W_T) \quad (4)$$

Where  $S_{Fi}$  is the fused similarity score,  $S_{NCi}$  is the normalized color feature similarity score,  $S_{NTi}$  is the normalized texture feature similarity score,  $W_c$  is the weight of color feature similarity score, and  $W_T$  is the weight of texture feature similarity score. By assigning appropriate values to  $W_c$  and  $W_T$ , a fine similarity score fusion can be gained.

## IV. SIMILARITY SCORE FUSION USING GENETIC ALGORITHM

During the course of similarity score fusion, a key problem is how to assign the weights of similarity score. It affects directly the retrieval performance of the system. It can be considered as an optimization problem to assign reasonably the weights of color feature similarity score and texture feature similarity score. That is to find the optimum in weight value space. So, this problem can be resolved by genetic algorithm. This paper proposed a similarity score fusion method using genetic algorithm. With genetic algorithm the weights of color feature similarity score and texture feature similarity score are assigned optimally.

### A. Determination of solution space

The aim of fusing similarity scores is to assign the weights of color feature similarity score and texture feature similarity score to gain a better image retrieval performance. With the consideration of (4), the weight of color feature similarity score  $W_c$  can be an integer between 0 and  $I$ , where  $I$  is a positive integer. Without loss of generality, the weight of texture feature similarity score can be assigned to  $I - W_c$ . The positive integer  $I$  determined the accuracy of solution. The bigger the value of  $I$  is, the higher the accuracy of solution is. But this may take a long time to resolve, and vice versa. To resolve using genetic algorithm, the weights should be encoded. The solution should be expressed as a binary number. So generally the value  $I$  is taken as  $2L$ , where  $L$  is a positive integer, the encoding length of the solution.

### B. Population Initialization

In genetic algorithm, the number of individuals in population and the initial values of the individuals will influence the solution greatly. In this paper, the number of individuals in population  $N$  is taken as  $I$ .  $N$  is set a bigger value, the aim of which is to gain the optimal solution quickly. The individuals are initialized as follows. The solution space is divided into  $N$  equal portions, the centers of which are taken as the initial values of the individuals.

### C. Determination of fitness function

The fitness of individuals can be evaluated as follows. According to the weights  $W_C$  and  $W_T$  of  $N$  individuals, we can get  $N$  groups of image retrieval results. For every group, the top  $M$  images are considered. Total number of images is  $MN$ . By calculating occurrence frequency of images of every group in all images, the fitness of every individual is evaluated.

### D. Solving for optimal solution

The genetic algorithm is implemented in classic mode. The condition for ending the iteration is that the number of iteration is equal to 3. When the iteration is ended, the maximum  $P^* = \max P_i$  is taken as the optimal solution. According to the optimal solution the weights  $W_C^*$  and  $W_T^*$  are assigned, then the image retrieval results with these two weights are taken as the ultimate retrieval results.

## V. CONCLUSIONS

This paper 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.

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