A Novel Adaptive Fuzzy Model for Image Retrieval

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Abstract: In many areas of commerce, medicine, entertainment, education, weather forecasting the need for efficient image retrieval system has grown dramatically. Therefore, many researches have been done in this scope; however, researchers try to improve the precision and performance of such system. In this paper, we present an image retrieval method, which uses color and texture based approaches for feature extraction, fuzzy adaptive model and fuzzy integral. The system extracts color and texture features from an image and enhancing the retrieval by providing a unique adaptive fuzzy system that use fuzzy membership functions to find the region of interest in an image. The proposed method aggregates the features by assigning fuzzy measures and combines them with the help of fuzzy integral. Experimental results showed that proposed method has some advantages and better results versus related ones in most of the time.

1 INTRODUCTION

In recent years the volume of digital images has grown dramatically. So, automatically storing and retrieving images together with fast and accurate searching has become a challenge among researchers.

In this way, a lot of researches have been done. Old methods were initially based on text. In the early 90s, Content-Based Image Retrieval (CBIR) was proposed. In general, the aim of CBIR, is to automatically extract visual features of images and perform retrieval based on these visual contents.

One of the most influential methods is SIMPLIcity (Wang et al., 2001). The base of the system is to classify images into categories semantically, such as textured-nontextured. It uses k-means clustering algorithm, wavelet-based feature extraction and LUV color space to segment an image into regions. It also developed an Integrated Region Matching (IRM) metric for finding similarity between regions.

Another well-known algorithm is ISLBP (Pandey and Kumar, 2011). ISLBP is an extension on LBP. LBP extracts features based on distribution of edges in the gray-scaled image. ISLBP extract LBP values from R, G and B channel spaces and by concatenating these features, it builds an inter LBP histograms and used them for image retrieval process.

It is quite clear that the same set of weights for different features is far from human perception and does not work well specially in the general-purpose image retrieval domain.

In this paper, we describe an efficient fuzzy-based approach to address a general purpose CBIR problem. The main novelty of proposed system is in proposing an adaptive fuzzy model which is placed on horizontal and vertical image strips and through them texture features are extracted. This model tries to find the region of interest in each image and increases the weight of the extracted features of that part. This will enable us to deal with different types of images and reduce the semantic gap.

The rest of the paper is organized as follows. Section 2, covers the structure of proposed method and feature selection process. Section 3 contains the proposed adaptive fuzzy model as a method for improving results of proposed signatures. Section 4 presents proposed approach for aggregation of the signatures. The obtained experimental results are given in Section 5 and section 6 concludes the paper.

2 THE PROPOSED METHOD ARCHITECTURE

Architecture of the proposed system follows the

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usual image retrieval systems, in such a way that it is formed by two main parts, the "Feature Extraction" and the "Search and Retrieval".

In retrieval system, after receiving the query image, its features are extracted by the "Feature Extraction" part and the feature vector is compared by entire database using a similarity measure, so the similarity of feature vectors of query image with all the database images is calculated. At the end, k nearest images to the query image is returned.

2.1 Feature Extraction Unit

The “Feature Extraction” unit is a key part in image database systems. However, depending on the method used and the application field, various features can be extracted.

2.2 Color Feature Extraction

For color feature extraction, we should first choose a suitable color model. For this work, we choose Lab color model because of its perceptual uniformity (have an equivalent distance in the color space corresponds to equivalent differences in color). In this method, at first the image is divided to some equal size blocks. Then from each block in the Lab space some features are extracted. For image blocking the most important issue is block size. For finding appropriate block size many simulations were carried out. Consequently, a 10×10 grid placed over each image. In each block of color, three color moments are computed per channel (9 moments). These moments are chosen because they are very efficient for quick search in image retrieval systems and also they are scale and rotation invariant.

Before putting these moment values in a histogram we normalized them by using (1).

$$X=\frac{X-X_{min}}{X_{max}-X_{min}} \qquad (1)$$

Where X_{min} and X_{max} are maximum and minimum between all values.

We used three 4-d histograms in such a way that each histogram includes the moments of L, a, and b channel. By doing this the spatial relation between these values is preserved in each pixel thus the relative quality of results improves.

2.3 Texture Feature Extraction

For taking advantage of both global and local characteristic of image, we use two methods for texture feature extraction.

For global texture we use Tamura texture features (Tamura et al., 1978). Tamura textures are six features which correspond to human visual perception: coarseness, contrast, directionality, line-likeness, regularity, and roughness. From experiments to test the importance of these features with respect to human perception, it was derived that the first three features are very significant, and the last three features are correlated to them and does not make much improvement in the results (Bergman, 2002). So, in proposed work we use coarseness, contrast, and directionality. We extract these features from each image and normalize them using (1). Finally a 3-dimension feature vector is generated for each image in the database and these vectors are compared using the Euclidean distance.

For local texture features we use Gabor filter. Gabor filters have been widely used for Texture analysis (Jain and Farrokhnia, 1991); (Daugman, 1988). Here we use mean and standard deviation descriptors derived from Gabor features. We extract Gabor features in four different orientations and four different scales that leading us to 32 values.

But prior to this it was necessary to divide the image to blocks. Unlike the color characteristics that square blocks were the best option available for them, this kind of blocks is not suitable for texture modelling. Rectangular blocks was a good choice because in many images, especially natural ones the rectangular strips were detected. Thus we segment each image to 20 rectangular horizontal blocks, and 20 rectangular vertical blocks. The blocks width is equal to 16 and its length is equal to the length and width of an image, respectively, for horizontal and vertical blocks. So, from each image 40*32=1280 values is extracted. We normalize these values using (1).

3 THE ADAPTIVE FUZZY MODEL

An issue that attracts our attention was that all extracted strips do not have equal weights. In other words, our beliefs in the importance of the various strips are different. So this issue encouraged us to use fuzzy logic to model this part of the work.

Generally in each image, the most important data is concentrated in the centre of the image and as we move away from the centre of the image the importance of the regions decreases, hence the significance of the strips will flowingly decrease. To model this complexity we define two membership functions (MFs) for each image, one on the x-axis for vertical blocks and the other on the y-axis for horizontal blocks. We have a variety of different options for the shape of MFs (Triangular, Rectangular, Gaussian, etc.). Gaussian MF is a good candidate because of its flexibility and in addition to that, in its Taylor series it contains other functions within itself, so we have chosen it.

To further improve the work and because of our region of interest that differs in each image, we should derive an optimum MF from a set of MFs which matches the image. Hence we need an adaptive mechanism. To achieve this goal, we considered different MFs on each axis so that, in each image, with respect to the distribution of objects one MF was chosen in each direction. We need a measure for choosing between different MFs, To do this after applying Gabor filter, we calculate the energy in different scale and orientation of each block. The more amount of this energy results in our firmer belief in the strips. For fuzzifying these values equation (1) is used.

To find the best MF on each axis and direction, the equation (2) can be used.

$$C(i) = \max_{i \in M} \sum_{k \in A} \mu 1_i(k) \times \mu 2(k) \qquad (2)$$

Where $\mu 1$ is the Gaussian MF, $\mu 2$ is the MF from the energy of each block, M is the set of Gaussian MFs, A is the center point of each block and C is the best MF among all MFs.

The operation was done here was in fact the operation between two MFs so that instead of using crisp operators (add and multiply), it is better to use fuzzy operators (max and min). So (2) is turn to (3).

$$C(i) = \max_{i \in M} \max_{k \in A} \min\{\mu 1_i(k), \mu 2(k)\} \qquad (3)$$

The remaining problem is to optimize the parameters of MFs.

The equation of the Gaussian MF is given by (4):

$$f(x) = \frac{\frac{1}{\sqrt{2\pi\delta^2}} e^{-\frac{1(x-\mu)^2}{2\delta^2}}}{Q\left(\frac{1-\mu}{\delta}\right) - Q\left(\frac{n-\mu}{\delta}\right)} \qquad (4)$$

$$Q(x) = \int_x^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \qquad (5)$$

Where μ is mean, and δ is variance.The other parameter is the area of the surface under the Gaussian curve. We set this parameter to one, because just in this case the narrowest MF contains only one block. The other parameter that should be set is (δ). Practically the least value for sigma, which belongs to the narrowest curve, should be selected. The reason is that it should be narrow enough to contain only one block. This value is equal to the $\frac{1}{\sqrt{2\pi}}$. The largest sigma is produced when our belief in all strips is equal, it is equal to half or total length of the image.

The other important parameter is evaluation of the rate of changes in Sigma. By sigma rate of change we mean the Sigma change between minimum and maximum of its amount per step.

This can be done in two ways arithmetic progression and geometric progression and we have evaluated both of them. As in figure 1 and in figure 2, narrower curves for smaller values of sigma were achieved in geometric progression and this is more suitable for us, and that is due to Gaussian Kernel, accordingly exponential change in the results will be better for us.

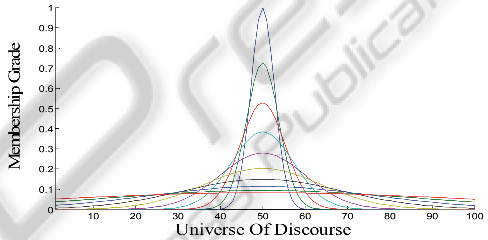

Figure 1: Gaussian membership functions with geometric progression of Sigma values.

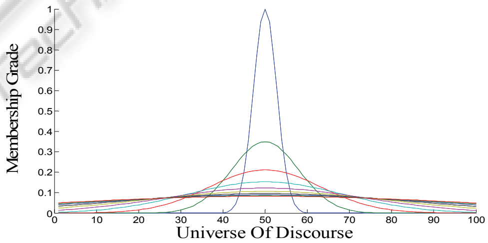

Figure 2: Gaussian membership functions with arithmetic progression of Sigma values.

Finally the mean and variance values obtained from each block were put in histogram and their frequencies were that of its MF value. Thus, from each image in every axis and every direction and every scale we have one histogram, which eventually gives us 64 histograms per image. These histograms are compared using the EMD (Rubner et al., 2000). So we built a hierarchical adaptive fuzzy model. In one layer of this hierarchical model, we have Gaussian MFs and in other layer we have energy MF. This model have two main advantages: first, it is visually abstract and second, the complexity of the system that is modelled is higher than the complexity of applying each layer individually.

4 RETRIEVING THE QUERY IMAGE

After receiving the query image from the user, the nearest images should be extracted and displayed to the user. To carry out this, feature vectors of images in the database are compared with the input image, and k-nearest images are shown to the user.

For comparing color histogram we used EMD, for Tamura texture features we use Euclidean distance and for Gabor feature histograms we used EMD. So for each feature, a number which representing the distance was calculated. For aggregation of these distances we use fuzzy integral (Mesiar, 2005). For using fuzzy integral, it is necessary to choose proper kind of integral. We have used the Choquet integral that is one of the best ones (Grabisch et al., 1992) in the proposed method.

We have a set with some distances, which each distance is a result of a feature extraction method. And a measure should be assign to each of them and any combination of them. The problem is that, these methods have some correlation and relation with each other, because we had two methods for texture extraction (Tamura and Gabor filter) and one method for color feature extraction (histogram of moments).

For assigning these measures we have used the following rules:

Rule 1: “The method with better performance attains a higher measure between 0 and 1”.

- If x_i and $x_j \epsilon$ A and

Efficiency (x_i) ≥Efficiency (x_j) then

$\mu(x_i) \geq \mu(x_j)$.

Rule 2: “The set which contains two methods which are less similar to each other and extract different features, their measure is super-additive”. Or,

- If x_i and $x_j \epsilon$ X and x_i and x_j are not similar, then $\mu(\{x_i, x_j\}) \geq \mu(x_i) + \mu(x_j)$.

Rule 3: “A set which contains two methods which are similar to each other and extract same features conceptually, their measure is sub-additive”. Or,

- If x_i and $x_j \epsilon$ X and x_i and x_j are similar, then $\mu(\{x_i, x_j\}) \leq \mu(x_i) + \mu(x_j)$.

One of the most important steps in the proposed method is assigning the appropriate measures that represent the relation between the methods.

Here, we have three different methods, which all of them were implemented separately. So, we had a good knowledge of the performance of each of them. By this knowledge and with the help of the rules mentioned before we assigned the proper measures.

For this set which has three members, seven measures are needed. Table 1 shows the assignments of the measures for each of the 7 combinations.

Table 1: Fuzzy integral measure assignment.

Combinations	Assignments
μ 1= μ ({d_{color}})	0.55
μ 2= μ ({d_{gab}})	0.38
μ 3= μ ({d_{tamura} })	0.07
μ 1,2= μ ({d_{color}, d_{gab}})	0.95
μ 1,3= μ ({d_{color},d_{tamura} })	0.70
μ 2,3= μ ({d_{gab}, d_{tamura}})	0.4
μ 1,2,3= μ ({d_{color}, d_{gab}, d_{tamura}})	1

On the basis of our simulations, we considered the following properties for attribution of measures: Color moment histogram performs the best, Gabor filter is the next and Tamura features performs the worst among these methods. In assigning measures to a double combination of these three methods, their structure and the category that each of them is belong to it, is important. Color moment and Gabor filter are quite separate and belong to different categories, so according to rule no. 2, their measure should be super-additive. To assign the measure to the pair of {d_{color},d_{tamura}}, the same description and rule is used. For assigning the measure to the pair of {d_{tamura},d_{gab}}, we should consider that both of these features try to extract the texture of the image, so they are in the same class, hence according to the rule 3, their assigned measure should be sub-additive.

After assigning these measures to the methods, Choquet integral was used to aggregate them. After performing the fuzzy integral, the final distance of two images was calculated.

As a final step, the first k images are shown to the user via user-interface.

5 EXPERIMENTAL RESULTS

We have tested our method with a general-purpose image dataset of about 1000 images of 10 semantic categories (Africans, Beaches, Buildings, Buses, Dinosaurs, Elephants, Flowers, Horses, Mountains, Foods) from COREL, which is called SIMPLIcity dataset. Each category includes 100 images.

We compare the accuracy of proposed method with SIMPLIcity and ISLBP. To provide results, we tested all of the images in the dataset. If the retrieved image belongs to the same category, is just considered as a match.

To get the efficiency of proposed method, we used the p (precision or average precision), as the comparison parameter (Wang et al., 2001). The experimental result is shown in Figure 3.

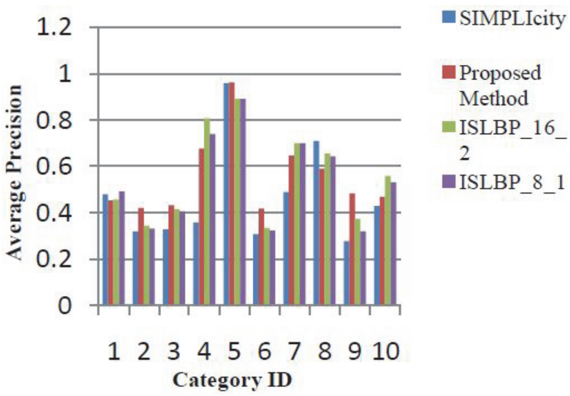

Figure 3: Comparing proposed method with SIMPLIcity and ISLBP methods on average precision.

It is clear that proposed method performs better than SIMPLIcity in all the classes except Africans, Buses and Horses classes. In comparison with ISLBP method, although it performs better than us in several classes, but its total average precision for all of the classes is 55.4 but our precision is 55.6, which shows that totally we performs better in this parameter.

6 CONCLUSIONS

This paper provides a new approach for image retrieval on the basis of fuzzy thinking. We integrate color and texture properties for image retrieval, and use fuzzy logic to improve the efficiency of the proposed method. The main contribution of our work is to adaptively weight different part of the region based on a hierarchical fuzzy model. This model can be easily extended to different features like color. We configure the model by tuning its different parameters. This configuration is extracted from the nature of problem. We also use fuzzy integral for improve our results.

For extending this framework, it is recommended to integrate proposed model with Content-Free Image Retrieval (CFIR) techniques (Yin et al., 2008), which is predicted to be the next generation of image retrieval systems.

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