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FSRM Feedback Algorithm based on Learning Theory

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Abstract: In order to narrow the "semantic gap" problem between the image low-level features and high-level semantic features, this paper proposed a FSRM algorithm based on the learning theory. To compress the dimension of FSRM, the algorithm divided the image database into "related" and "irrelevant" two classes by retrieval of low-level features image. Then, adjust the weights in FSRM based on user feedback. Finally, after a finite time feedback, adjust the weights in FSRM using the learning theory FSRM algorithm, and returned the new retrieval results to the user. The experiment shows that this algorithm can express the semantics contained in the image, also can be a good description of the semantic similarity between images, therefore, the proposed algorithm has certain robustness.

Keywords: Image retrieval, Semantic gap, Relevance feedback, FSRM, Semantic similarity.

1. INTRODUCTION

With the development of multimedia technology and internet, a vast multimedia information ocean appeared in front of people, and further lead to the super large image information base. The problem, how to effectively help people to find the needed information quickly and accurately , has become the core problem to be solved in image retrieval system[1]. The low-level features such as color and texture are not always accurately reflect the human visual perception of the high-level concept in CBIR. Feedback technology, which exactly solves the "semantic gap" problem underlying semantic features between images, has attracted the attention of many scholars. So far, the relevance feedback technology in the CBIR is broadly divided into two categories [2,3]:One is adjusting some of the parameters in similarity measure based on the user's feedback information; the other is from a probability standpoint, calculating the probability of each image in the image library which meets user requirements, and taking the high probability images as the search results returned to the user.Cox[4] and Nuno[5] assumed that positive, negative feedback image is a series of independent retrieval unit for a given query image, and tried to minimized the retrieval error by using Bayes rule to optimize the search results. Rui and Huang proposed a feature standard deviation algorithm [6,7], the basic idea is that in the feature space, reduce the feature weights of larger distribution standard deviation, whereas increased weights to improve retrieval effect. At the same time they proposed a multilevel image model, and deal with the problem of adjusting the weights by using global optimization methods based on the model. This paper presents a feedback algorithm based on fuzzy semantic relevant matrix (FSRM). The specific approach are: Firstly, divide the image library into relevant and irrelevant image categories by using low-level visual features; Secondly, adjust the weights in the FSRM in accordance with the relevant or irrelevant images user labeled; Finally after a limited feedback times , further amendment FSRM matrix elements through learning theory, thus the better retrieval results can be obtained. The proposed algorithm in this paper is feedback based on FSRM, so no prior knowledge of specific issues needed, convenient to implement, and will achieve better search effect under the condition of limited feedback times.

2. FSRM FEEDBACK ALGORITHM

2.1 FSRM theory

In 1965, the theory of fuzzy mathematics, presented by Zadeh, is used to study the problem of fuzzy uncertainty, which expanded the characteristic value scope of the set {0,1} to the interval [0,1] of continuous values. So we can use value in the interval [0,1] to represent a certain extent which one object meet some concept. The closer the object corresponding value to 1, the greater the degree of compliance with the concept; On the contrary, the smaller the degree of compliance.

The Fuzzy Matrix A is defined as[2,8] :

$$A=(a_{ij})_{m\times n}, \text{ and } a_{ij}\in[0,1](i = 1,2,...m;j = 1,2,...,n)$$

Because of the ambiguity of human language and semantics, it is very difficult for us to completely des cribe the image with precise semantics or literal, using the fuzzy semantic relevance matrix (FSRM) to build the semantic bridge [3], the FSRM elements satisfy the equation(1):

$$R(i,j)\in[0,1], R(i,j)=1, \quad and \quad R(i,j)=R(j,i), i,j=0,1,...,N-1 \quad (1)$$

Where, N is the number of images in the Image Library. R(i,j), the direct similarity, reflects the similarity between two images i and j. FRSM is a Fuzzy similar matrix according to the definition of fuzzy matrix.

The size of FSRM is decided by the number of images in the image library, thus the FSRM is a very large matrix for a large image library, and so the corresponding computation will be enormous. In order to reduce the size of the FSRM, this paper firstly classify image library into two classes of relevant and irrelevant, and then a FSRM is established for each class, thus the size of FSRM is greatly reduced.

2.2 FSRM feedback algorithm description

For each class of image library, R (i, j), the similarity of image i and j , is represented by the element of FSRM, and FSRM is initialized to a symmetric matrix :

$$0 \le R(i,j) \le 1(i,j=1,2,...,N) \quad if \quad i=j \quad then: \quad R(i,j)=1$$
$$otherwise \quad R(i,j)=R(j,i)(i,j=1,2,...,N) \tag{2}$$

Where, N is the number of each image library. Because there are some similarities between the images for each image category, the initial value of FSRM will be set to the vaguest value of 0.5 between 0-1 , that is R(i,j)=0.5(i≠j and i□j□1□2□…□N). During FSRM feedback process, for the relevant image class (I +) in the same image library, the corresponding weights in FSRM are adjusted according to the equation (3), or do not modify; Unrelated image class (I-) in the same image library, the corresponding weights in FSRM are adjusted according to the equation (4).

$$R(i,j)_{new} = R(i,j)_{old} + \alpha(1 - R(i,j)_{old}) \tag{3}$$

$$R(i,j)_{new} = R(i,j)_{old} - \beta(1 - R(i,j)_{old}) \tag{4}$$

Where, α, β respectively expressed the degree parameter weights increased or decreased, and satisfy α+β=1. Select α=0.35 and β=0.65 .

With FSRM weight adjustment equations, we can get the experimental procedures using FSRM for retrieval, the specific steps are:

(1) Initialize the FSRM.

(2) After research based on low-level visual features , choose the former K (K<N) images as the search results returned to the user, the users label the k images as the current relevant image database I^{+}_{1} , the remainder being irrelevant image database I^{-}_{1}.

(3) According to the equation (3) and (4), adjust each class of the image library weights respectively in its FSRM.

(4) Partial weights of each image library in FSRM have been made from an initial value of 0.5 to a more realistic semantic value after training through a limited times of step 3, that is to say, a certain similarity has been established between images in each image class, then modify the semantic matrix by learning each of the FSRM data according to the 2.3 section algorithm, and then return the results back to the user.

(5) According to the user feedback, mark the corresponding image in FSRM with the weights from big to small order, return the most similar images to the user, if the user is satisfied, then save the results, terminate the retrieval. Otherwise, go to the second step again until the feedback results to meet user needs.

2.3 Learning FSRM feedback algorithm

There is a certain gap between similarity of low visual features and semantic similarity in image retrieval, therefore, the memory and learning of semantic information plays an important role to improve the performance of retrieval system. As can be seen from the experiment, after a finite number of feedback times, some weights of each fuzzy semantic relevant matrix have been from the initial value (0.5) to semantic weights. Fig.(1) shows the top 10 fuzzy semantic correlation between the image and the query image in a FSRM after several feedback by using the algorithm of section 2.2 (weights matrix elements are rounded to retain two decimal places).

	1	2	3	4	5	6	7	8	9	10
1	1	0.5	0.79	0.5	0.86	0.5	0.5	0.91	0.5	0
2	0.5	1	0.5	0.5	0.5	0.5	0.91	0.5	0.5	0.5
3	0.79	0.5	1	0.68	0.5	0.91	0.5	0.5	0.5	0.86
4	0.5	0.5	0.68	1	0.5	0.5	0.68	0.5	0.5	0.5
5	0.86	0.5	0.59	0.5	1	0.5	0.18	0.5	0.18	0.5
6	0.5	0.5	0.91	0.5	0.5	1	0.5	0.46	0.5	0.5
7	0.5	0.91	0.5	0.68	0.18	0.5	1	0.5	0.86	0.5
8	0.91	0.5	0.5	0.5	0.5	0.46	0.5	1	0.5	0.5
9	0.5	0.5	0.5	0.5	0.18	0.5	0.86	0.5	1	0.5
10	0.5	0.5	0.86	0.5	0.5	0.5	0.5	0.5	0.5	1

Fig. (1). FSRM Matrix before Learning.

The elements in Fig.(1) represent the direct similarity between respective images. As can be seen, after several feedback times, R (7,4) is updated to 0.868 from the initial value of 0.5, R (3,6) is updated to 0.91, but R (5,3) is still the initial value 0.5 no change because of the limitation of the feedback frequency, this indicates that it is difficult to reflect their semantic similarity implied for the "direct similarity" R(5,3). In comparison, R (5,1) * R (1,3) = 0.6794 can better reflect the hidden semantic information between image 5 and image 3. It is necessary for the hidden semantic information embodied in FSRM for better research effect. The semantic similarity is defined as equation (5):

$$\begin{aligned} &if \quad R(i,k) \ge T, R(k,j) \ge T, R(i,k)*R(k,j) \ge T \\ &and \quad R(i,k)*R(k,j) \ge R(i,j) \ge 0.5, \\ &then \quad R(i,j) = R(i,k)*R(k,j) \qquad (i \ne j) \end{aligned} \tag{5}$$

Where, T is a threshold value, and is taken 0.5 in the experiment.

Through the study of the above methods, the weights in Fig.1 is adjusted to the results in Fig.(2) (element weights rounded to retain four decimal places). As can be seen from Fig.(2), after limited feedback learning, element in FSRM updates faster, and as a result is closer to the reality of semantic similarity, thereby further improving the retrieval performance of the system.

	1	2	3	4	5	6	7	8	9	10
1	1	0.5	0.79	0.5	0.86	0.5	0.5	0.91	0.5	0.5
2	0.5	1	0.5	0.5	0.5	0.5	0.91	0.5	0.5	0.5
3	0.79	0.5	1	0.68	0.6794	0.91	0.5	0.5	0.5	0.86
4	0.5	0.5	0.68	1	0.5	0.5	0.68	0.5	0.5	0.5
5	0.86	0.5	0.6794	0.5	1	0.5	0.18	0.7826	0.18	0.5
6	0.5	0.5	0.91	0.5	0.5	1	0.5	0.46	0.5	0.5
7	0.5	0.91	0.5	0.68	0.18	0.5	1	0.5	0.86	0.5
8	0.91	0.5	0.5	0.5	0.7826	0.46	0.5	1	0.5	0.5
9	0.5	0.5	0.7189	0.5	0.18	0.5	0.86	0.5	1	0.5
10	0.5	0.5	0.86	0.5	0.5	0.5	0.5	0.5	0.5	1

Fig. (2). FSRM Matrix after Learning.

3. EXPERIMENTAL RESULTS AND ANALYSIS

3.1 Experimental environment

The simulation experiment is based on MATLAB platform, image library compose of two types of images: character images (50 images) and flower image (50 images). Image size is 480×640 in each image database, image format is JPG. In experiment, randomly select around five individuals from colleagues for each class image library to retrieve two times. The user will be let mark the result image as “relevant” or “irrelevant” class according to his requirements in each feedback.

3.2 Experimental results analysis

Experimental analysis consists of two parts: One part is effectiveness comparison of the three algorithm based on low level visual features (selected texture feature in the experiment), no relevant feedback learning and relevant feedback learning; Another part is studying effectiveness of the proposed algorithm from the perspective of the number of feedback. Fig.(3)- Fig.(5) shows the 8 most similar images for the retrieval of flower database. Fig.(3) gives the retrieval results based on low level visual features(texture features); Fig.4 gives the retrieval results based on the no relevance feedback learning, only adjust the weight in FSRM according to the user's feedback information; Fig.(5) shows the results based on learning algorithm after a limited feedback times using no relevance feedback learning algorithm. The learning algorithm can effectively improve the performance of the system by comparison of Fig.(4) and Fig.(5). Fig.(6)-Fig.(7) gives relationship curve the average feedback precision and the number of feedback. Feedback precision is defined as equation (6):

$$P = a / b \tag{6}$$

Where, a is the number of relevant image ranked in the top K, b is the number of image ranked in the top K.

As Fig. (6) and Fig. (7)is shown intuitively, the algorithm of learning FSRM further improve the effectiveness of the retrieval system.

Fig. (3). Retrieval Results based on Low Level Visual Features.

Fig. (4). First Retrieval Results before Learning.

Fig. (5). First Retrieval Results after Learning.

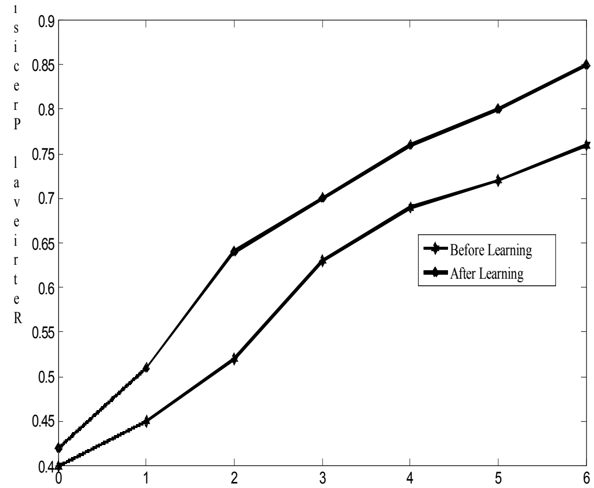

Fig. (6). Feedback Precision of Character.

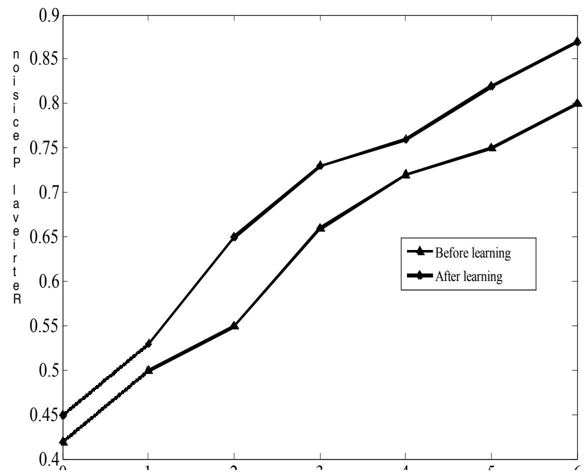

Fig. (7). Feedback Precision of Flower.

4. CONCLUSION

Relevance feedback plays an important role in image retrieval; therefore this paper applies the fuzzy semantic relevant matrix to relevance feedback of image retrieval, and proposes a FSRM feedback algorithm based on the learning theory. Firstly the algorithm classified image library into two classes of relevant and irrelevant by using low level visual features to retrieval, and then a FSRM is established for each class, thus the size of FSRM is greatly reduced; Again, constantly adjust the weights in FSRM for each class according to the user' feedback information; Finally, further update the weights in FSRM based on the learning proposed in section 2.3 after a limited feedback times using no relevance feedback learning algorithm, thus the weights will be closer to the semantic features. Experimental results show that the proposed algorithm solves the "semantic gap" problem between low-level features and high-level features to a certain extent, and has certain application value.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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