A Novel Image Retrieval Algorithm Based on Adaptive Weight Adjustment and Relevance Feedback

Shu-qin Liu
School of Information Science and Technology Northwest University, Xian, China
lsqnate@163.com

Jin-ye Peng
School of Information Science and Technology Northwest University, Xian, China
lsynate@163.com

***Abstract*—Weighted coefficients of image retrieval algorithm based on relevance feedback are determined in advance, which is lack of flexibility. In order to obtain satisfactory retrieval results, this algorithm requires a large amount of feedback calculation and efficiency of the algorithm is low. Aiming at the faults of relevance feedback, the adaptive adjustment algorithm of weighted coefficients based on quantum particle swarm optimization is presented, which is composed of user feedback process and particle evolution process. The particle encoding process and fitness function calculation process are worked out. The result of experiment using the Corel standard library, shows that quantum particle swarm optimization algorithm greatly improves the retrieval accuracy than the other image retrieval algorithms.**

***Index Terms*—relevance feedback, quantum particle swarm optimization, detection accuracy, weight adjustment**

I. INTRODUCTION

Content Based Image Retrieval(CBIR) starts from the content of images and supplies more effective retrieval methods to automatically retrieve images satisfying users' requirements[1,2]. CBIR involves with many subjects including image processing, pattern recognition, computational intelligence, database, and so on, and it has been paid attention all the time[3]. Along with the development of computer, multimedia, network, and digital communications, effective image retrieval algorithms have been applied in many fields closely interrelated with people's life, such as image retrieval engine, network environment purification, safe city construction, safe production monitoring, key frame extraction, and many other specialized fields[4].

The research of retrieval algorithms include the key technologies of feature extraction, similarity matching, relevance feedback(RF), and so on. Along with the development of research and the increasingly complex applications, CBIR desires more intelligent and effective algorithms, so exploring new intelligent methods becomes an important research content in CBIR field[5,6]. Relevance feedback technology is introduced into image retrieval, and becomes the effective method to improve the retrieval performance. Many methods have been proposed for the RF problem[11-18]. Zhang proposed a RF algorithm based on the forward neural network from the perspective of machine learning. Deselaers etc proposed a RF method based on classifier combination, which could automatically adjust the weight of distance function of CBIR at the same time.Vasconcelos took RF as a Bayesian inference problem, and positive and negative feedback were treated equally. In order to overcome the problem of too little training samples and asymmetry of positive and negative samples, Wu proposed a Bayesian active learning mechanism. Grigorova acquired the proper characteristic weight by RF, and at the same time the parameters were dynamically selected. Qiu Zhaowen etc proposed a RF algorithm based on quadratic distance. Su etc proposed a RF algorithm based on Bayesian classifier, using different feedback strategies to deal with positive and negative feedback respectively. Although these RF algorithms have achieved a certain retrieval effect, there are some problems. The current CBIR technology mainly retrieve image based on example query method, and algorithms generally assume that retrieve goal is clear. However, in actual CBIR, user has vague understanding of target before retrieve. The initial feedback of user in the algorithms are based on a specific retrieval algorithm, and the first retrieval results have a great influence on feedback of user and understanding of user to the image library, which leads to feedback effect having a lot of limitations[19-23]. Algorithms mostly adjust parameters according to the scheduled criterion, and parameter adjustment scale depends on the scheduled criterion, which has no flexible adaptive adjustment space. In order to get good retrieval effect, algorithms are bound to do multiple feedback operation, while too much feedback inevitably makes the efficiency of the algorithm low. Quantum particle swarm optimization algorithm can overcome the problems of the above, which has flexible, intelligent and efficient advantages. QPSO algorithm is

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introduced into RF field, and quantum particle swarm optimization relevance feedback based on image encoding is proposed. A kind of quantum particle swarm optimization relevance feedback algorithm based on weight adjustment is proposed.

RF is a semi-automated query optimization strategy, but the particularity of the RF application in CBIR is different from other learning problems, such as the fewer training sample, high real time requirement, asymmetry of the training sample, and a lot of unlabeled samples. Architecture of relevance feedback algorithm is shown in Fig. 1. QPSO algorithm is one of effective methods solving optimization problem which has the following advantages. For QPSO algorithm, usually 10-20 feedback samples are enough to effective guidance for evolution direction of group. The fast convergence of the QPSO algorithm can ensure the retrieval efficiency of the RF. RF often uses the way of marking positive samples, and is lack of studying negative samples, and QPSO algorithm has no special demand to the symmetry of sample, QPSO algorithm performs global search in the solution space, and is not easy to fall into local minimum, so a large number of labeled samples will be searched and fed back. Therefore, the characteristics of QPSO algorithm determines that it has very good feasibility in RF, but the good combining site selection and design of the QPSO and CBIR are more difficult. Using QPSO algorithm to solve RF problem needs to design good meeting point in particle coding, continuity of space, optimized constraint conditions, assessment criteria and termination conditions. In image retrieval application, first of all, for any image A_i, feature extraction is performed, and N' types of features are got, which is labeled as C_j, $j=1,2,\ldots,N'$. The j-th feature is $C_j=(C_j^1,C_j^2,\ldots,C_j^{n_j})^T$. n_j is dimension of feature C_j. Each component C_j^k ($k=1,2,\ldots,n_j$) of C_j is encoded with a real number corresponding to a bit code X_i^p of particle. Particle code of image A_i is $X_i=(X_i^1,X_i^2,\ldots X_i^Q)$, $Q=\sum_{j=1}^{N} n_j$. Solution space of QPSO is continuous, which is $Y=f(x), Y\in S$. Solution space $s'=\{A_1,A_2,\ldots,A_{n'}\}$ of RF is discrete. A_i represents the i-th image in image library and n' represents the size of image library. For a continuous solution, discrete solution $y^*=\arg\min_{y'}\{D(y,y')\}$ is taken as optimal solution, $y\in s, y'\in s'$. Combined with the actual CBIR problems, in order to ensure particles to evolve to the optimal direction. Global best position $gBest$ is calculated by (1) and it is average position of N_1 pieces of images fed back by user.

$$gBest = average(X_i) \tag{1}$$

$i=1,2,\ldots,N_1$ and N_1 represents the number of image fed back by user. The optimal criteria and termination condition of QPSO is clear, but the optimal standard itself is very fuzzy for CBIR problem, and the user's subjective uncertainty makes the goal determination of retrieval gradually clear with the whole process of retrieval. $gBest$ will exist fluctuation adjustment in a certain range, when a user goal is gradually stabilized, evolution of the particle can be terminated. When results of R_k and R_{k+1} are similar, evolution is terminated. In addition, definition domain of particle need to meet constraint conditions, which makes the quantum particle swarm optimization evolution must be carried out under certain constraints, and can be achieved by normalization method to ensure particle position within constraint characteristic scope after evolution.

In the next section, relevance feedback based on quantum particle swarm optimization is proposed. In Section 3 we adjust weights based on quantum particle swarm optimization algorithm. In Section 4, In order to check effectiveness of quantum particle swarm optimization relevance feedback algorithm, we do two experiments using Corel image library. In Section 5 we conclude the paper and give some remarks.

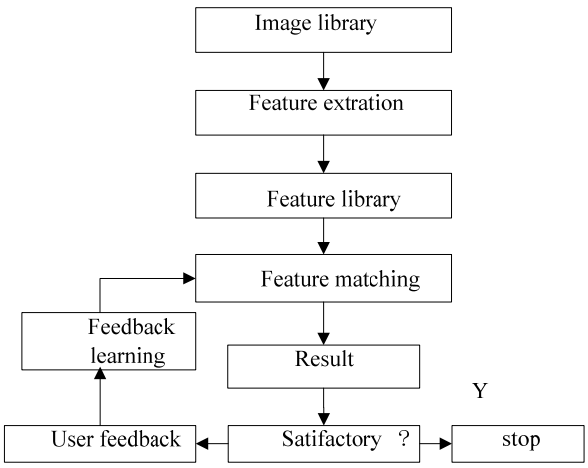

Figure1. Architecture of relevance feedback algorithm

II. Relevance Feedback Based On Quantum Particle Swarm Optimization

Quantum particle swarm optimization relevance feedback based on image encoding is made up of two layers of user feedback and particle evolution. When feedback is demanded, particle swarm X_i, $i=1,2,\ldots,N$ is initialized. X_i represents image which is randomly extracted from image library and N is size of swarm. Speed component of v_i is defined in (2).

$$v_i^k = rand(FeatureDomain^k) \tag{2}$$

v_i^k is initial speed of the k-th component of particle X_i. $FeatureDomain^k$ is definition domain of the k-th component of particle X_i. User selects relevant N_1 pieces of image as a feedback result according to the expected target and uses average position of N_1 pieces of image as current optimal position $gBest$ to guide evolution direction of particle. Position and speed are adjusted according to fitness value $E(X_i, gBest)$. $E(\cdot,\cdot)$ is weighted distance corresponding to feature code and evolution result is shown in (3).

$$X_i = \{\arg\min_{\bar{X}_j}(E(\bar{X}_j, X_i)), \bar{X}_j \neq X_k, k < i\} \tag{3}$$

$i = 1, 2, \ldots, N$. $\bar{X}_j$ represents discrete image coding in the image library. The process of particle swarm optimization relevance feedback based on image encoding is as follows.

Step1. User feedback parameter is initialized including population size N, particle swarm X_i, $i = 1, 2, \ldots, N$, iteration times M and feedback count $f = 0$.

Step2. If it meets feedback termination condition as shown in (4), feedback stops. Otherwise, $f = f + 1$ and turn to step 3.

$$\left|gBestUser(f) - gBestUser(f-1)\right| < \varepsilon \tag{4}$$

Step3. v_i is initialized according to (2) and $gBest$ is initialized according to (1). $gBestser(f) = gBest$, $pBest_i = X_i$ and $t = 1$. Then calculate $E(X_i, gBest)$.

Step4. if (5) is established, $pBest_i = X_i(t)$

$$E(X_i(t), gBest) < E(pBest_i, gBest) \tag{5}$$

Step5. v_i and X_i are updated according to (6) and (7).

$$\begin{aligned} v_i(t+1) &= wv_i(t) + c_1 r_1(t)(pBest_i(t) - x_i(t)) \\ &+ c_2 r_2(t)(gBest(t) - x_i(t)) \end{aligned} \tag{6}$$

$$x_i(t+1) = \begin{cases} p_i - L \cdot \ln(\frac{1}{u}), & rand() > 0.5 \\ p_i + L \cdot \ln(\frac{1}{u}), & rand() \leq 0.5 \end{cases} \tag{7}$$

$$p_i = r \cdot pBest_i(t) + (1-r) \cdot gBest(t).$$

$$L = \alpha\left|x_i(t) - mbest\right|, mbest = \frac{1}{N}\sum_{i=1}^{N} pbest_i.$$

u and r are uniformly distributed random numbers between 0 and 1. α represents contraction or expansion coefficient.

Step6. If $t > M$ or $X_i(t+1) - X_i(t) < \varepsilon$, particle evolution stops and turns to step 7. Otherwise $X_i(t) = X_i(t+1)$, $t = t+1$ and it turns to step 5.

Step7. Evolution result is shown according to (3) and it turns to step 2.

III. A Novel Particle Swarm Optimization Relevance Feedback Based On Weight Adjustment

Relevance Feedback technology mainly includes the method based on distance measurement, the method based on probabilistic framework, and the method based on machine learning. Supposing original image vector is Q, query vector is Q', the number of total relevant images is N_P, the number of total irrelevant images is N_F, relevant image set is $\{I_i^+ \mid i = 1, \ldots, N_P\}$, and irrelevant image set is $\{I_i^- \mid i = 1, \ldots, N_F\}$. α, β and γ are constants. Adjustment formula of query vector is (8). Another kind of feature weight adjustment method is to adjust weight optimization results of the feature. Weighted distance is shown in (9).

$$Q' = aQ + \beta(\frac{1}{N_P}\sum_{i=1}^{N_P} I_i^+) - \gamma(\frac{1}{N_F}\sum_{i=1}^{N_F} I_i^-) \tag{8}$$

$$D = (x_i, q, w) = \sum_{j=1}^{n}(w_j \cdot dis(x_{ij}, q_j)) \tag{9}$$

$q = (q_1, q_2, \ldots, q_n)^T$ represents query vector and $x_i = (x_{i1}, x_{i2}, \ldots, x_{in})^T$ represents feature. $dis(\cdot,\cdot)$ represents distance between x_{ij} and q_j.

$$S' = \left\{ x_i \mid dis((\alpha,\beta,\gamma)\begin{Bmatrix} S \\ \frac{1}{N_P}\sum_{i=1}^{N_P} I_i^+ \\ -\frac{1}{N_F}\sum_{i=1}^{N_F} I_i^- \end{Bmatrix} \cdot w, x_i \cdot w) < \varepsilon \right\} \tag{10}$$

$$= \left\{ x_i \mid dis((\alpha,\beta,\gamma)\begin{Bmatrix} S \\ D_R' \\ -D_N' \end{Bmatrix} \cdot w, x_i \cdot w) < \varepsilon \right\}$$

$$S' = \left\{ x_i \mid \begin{pmatrix} dis'(\alpha C_{1s} + \beta C_{1D_R'} - \gamma C_{1D_N'}, x_{i1} \\ dis'(\alpha C_{2s} + \beta C_{2D_R'} - \gamma C_{2D_N'}, x_{i2} \\ \vdots \\ dis'(\alpha C_{ns} + \beta C_{nD_R'} - \gamma C_{nD_N'}, x_{in} \end{pmatrix} \cdot (w_1, w_2, \ldots, w_n) < \varepsilon \right\}$$

$$= \left\{ x_i \mid \sum_{j=1}^{n}(w_j \cdot dis'(\alpha C_{js} + \beta C_{jD_R'} - \gamma C_{jD_N'}, x_{ij})) < \varepsilon \right\}$$

w is weighted coefficient. Query vector adjustment formula and feature weight adjustment formula can be combined together to form the final retrieval results, as is

shown in (10). S' is optimized query result and S is initial query. and S, D_R, D_N can be represented by $(C_{1S}, C_{2S}, \ldots, C_{ns})^T$, $(C_{1D_R'}, C_{2D_R'}, \ldots, C_{nD_R'})^T$, $(C_{1D_N'}, C_{2D_N'}, \ldots, C_{nD_N'})^T$. $D_R' = \frac{1}{N_P}\sum_{i=1}^{N_P} I_i^+$, $D_N' = \frac{1}{N_F}\sum_{i=1}^{N_F} I_i^-$, and $w = (w_1, w_2, \ldots, w_n)$ represents initial weights, which are encoded with random real number belonging to $[0,1]$. X_i is defined as follows.

$$X_i = (w_1, w_2, \ldots, w_n)$$
$$w_j = rand(wDomain),\ j = 1, 2, \ldots, n \tag{11}$$
$$wDomain = [0,1]$$
$$\sum_{j=1}^{n} w_j = 1$$

n is dimension of feature of image. The value of initial speed v_i is shown as follows.

$$v_i = (v_{w_1}, v_{w_2}, \ldots, v_{w_n})$$
$$v_{w_j} = sign(rand(0,1) - 0.5) * rand(wDomain) \tag{12}$$
$$wDomain = [0,1]$$
$$\sum_{j=1}^{n} \left| v_{w_j} \right| < 1$$

$pBest_i$ is local optimal weight parameter. $gBest$ is global optimal weight parameter. Design of fitness function is as follows.

The key point of QPSO evolution algorithm is guidance of the evolution direction, which evaluates the results through fitness function. In RF problem, user feedback is guiding basis for optimal evolution, so the positive and negative samples fed back by user can guide the evolution direction. For positive samples, uniform distribution of feature component reflects the common feature direction of user, and weight of feature should increase. For difference characteristic of goal, weights should be reduced. Supposing positive sample is $E_1, E_2, \ldots, E_{N_R}$ and its feature vector is $(C_1^i, C_2^i, \ldots, C_n^i)^T, i = 1, 2, \ldots N_R$. Negative sample is $U_1, U_2, \ldots, U_{N_N}$ and its feature vector is $(C_1'^i, C_2'^i, \ldots, C_n'^i)^T, i = 1, 2, \ldots N_N^T$. N_R is the number of positive samples and N_N is the number of negative samples. Fitness function is defined as follows.

$$fit(X_i) = fit_r(X_i) - fit_{ur}(X_i) \tag{13}$$

$$fit_r(X_i) = sim(norm(\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2), norm(w_1^j, w_2^j, \ldots, w_n^j))$$
$$\sigma_1^2 = \sigma^2(C_1^1, C_1^2, \ldots, C_1^{N_R})$$
$$\sigma_2^2 = \sigma^2(C_2^1, C_2^2, \ldots, C_2^{N_R})$$
$$\sigma_n^2 = \sigma^2(C_n^1, C_n^2, \ldots, C_n^{N_R})$$
$$fit_r(X_i) = sim(norm(\sigma_1'^2, \sigma_2'^2, \ldots, \sigma_n'^2), norm(w_1^j, w_2^j, \ldots, w_n^j))$$
$$\sigma_1'^2 = \sigma^2(C_1'^1, C_1'^2, \ldots, C_1'^{N_R})$$
$$\sigma_2'^2 = \sigma^2(C_2'^1, C_2'^2, \ldots, C_2'^{N_R})$$
$$\sigma_n'^2 = \sigma^2(C_n'^1, C_n'^2, \ldots, C_n'^{N_R})$$

$fit_r(X_i)$ represents matching degree between particle and variance distribution of feature component of positive sample and $fit_{ur}(X_i)$ represents matching degree between particle and variance distribution of feature component of negative sample. σ^2 denotes variance and $norm(\cdot)$ denotes normalized vector norm. The process of proposed algorithm is as follows.

Step1. Feedback parameter is initialized $f = 0$ and the number of results is Z. Z pieces of images are randomly selected as initial detection results.

Step2. Evolution parameter of particle is initialized including size of swarm N, iteration times M of particle swarm. Particle swarm is initialized according to (11). Speed of particle swarm is initialized according to (12). Local optimal value $pBest_i = X_i$ and global optimal value is $gBest = X_1$. The number of generation of evolution is $t = 1$.

Step3. Calculate fitness value according to (13).

Step4. Adjust optimal position $pBest_i$ of individual according to (14) and then adjust global optimal position $gBest$ according to (15).

If $fit(X_i) > fit(pbest_i)$,

$$pbest_i = X_i. \tag{14}$$

If $fit(pbest_i) > fit(gbest)$,

$$gbest = pbest_i. \tag{15}$$

Step5. Update v_i and X_i according to (6) and (7).

Step6. If it meets evolution termination shown in (16), evolution stops. Otherwise it turns to step 3.

$$\sum_{i=1}^{N} \left| X_i(t+1) - X_i(t) \right| < \varepsilon \tag{16}$$

Step7. Display the retrieval results. If user is satisfied the current results, feedback stops. Otherwise $f = f + 1$ and it turns to step 2.

IV. Experiment And Analysis

In order to test retrieval results of quantum particle swarm optimization relevance feedback based on image encoding(QPSO-IE), Corel standard image library is chosen for experiment, which includes 1000 pieces of images and includes 10 categories such as africa, beaches, monuments, busses, dinosaurs, elephants, flowers, horses, mountain, and cookie/food. Each category includes 100 pieces of images. Size of swarm is $N = 50$, and iteration times of particle swarm M in one feedback is 30. Weight decreases from 0.9 to 0.2 linearly. Learning factor is $c_1 = c_2 = 0.5$. r_1 and r_2 are random numbers between 0 and 1. Classic 72 dimension quantitative color histogram feature is selected to encode the particles. In this section retrieval accuracy of the different feedback phase has been analyzed in the experiment. Relation between iteration times and detection accuracy is shown in Fig.2. The horizon axis represents iteration times and vertical axis represents detection accuracy.

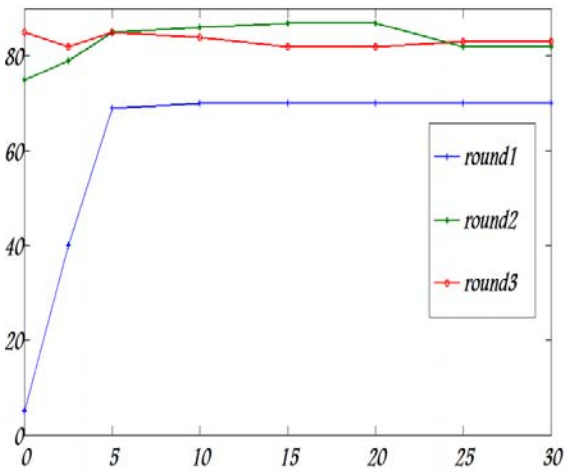

Figure2. Relation between iteration times and detection accuracy

TABLE I
ACCURACY COMPARISON OF DIFFERENT ALGORITHMS

round	Bayesian[21]	Content-based[22]	Learning weighted distances[23]	QPSO-IE
round0	-	0.222	0.115	0.097
round1	0.520	0.467	0.422	0.810
round2	0.660	0.598	0.641	0.885
round3	0.710	0.693	-	0.893

After the first round of feedback, with the increasing of number of particle evolution generation, retrieval precision increases gradually and is stabilized. After the second round of feedback, retrieval precision is further improved and is stabilized again. After the third round of feedback, retrieval accuracy is basically smooth and satisfies the convergence condition and evolution stops.

In order to further verify the effectiveness of the QPSO-IE algorithm, QPSO-IE algorithm are compared with other RF algorithm[21-23]. In the experiment, accuracy evaluation index is the same. Top20 accuracy comparison is shown in TABLEI.

TABLE II.
AVERAGE FEEDBACK ACCURACY OF DIFFERENT CATEGORIES OF IMAGE IN FIVE ROUNDS

caterory	round1	round2	round3	round4	round5
africa	0.701	0.602	0.604	0.616	0.638
beaches	0.500	0.558	0.603	0.621	0.584
monuments	0.358	0.464	0.422	0.516	0.502
busses	0.720	0.843	0.819	0.824	0.844
dinosaurs	1	0.975	0.980	0.980	0.980
elephants	0.363	0.419	0.380	0.381	0.484
flowers	0.301	0.384	0.443	0.380	0.404
horses	0.916	0.903	0.860	0.920	0.921
mountain	0.343	0.441	0.500	0.403	0.420
cookie/food	0.659	0.758	0.702	0.744	0.704
average	0.5861	0.6347	0.6313	0.6385	0.6481

It can be seen from TABLEI, initial accuracy of QPSO-IE before feedback is only 0.097, but after the first round of feedback, the improvement amplitude of retrieval precision of QPSO-IE is much higher than other methods, and the precision after each round of feedback are superior to other methods. Average feedback accuracy of different categories of image in five round of feedback is shown in TABLEII. It can be seen from TABLEII, with the increasing of number of feedback round, the retrieval accuracy is gradually improved, which shows that automatic evolution search process of quantum particle swarm optimization can combine with user feedback cognition efficiently and can search image library completely to meet user requirements. In the feedback process, since specificity of each feedback results and content of some images are chaos, so it can make retrieval accuracy fluctuate within a certain range. But it has no effect on the increasing trend of the average retrieval accuracy, and the overall average retrieval precision converges to more than 0.6 after repeated feedback.

In order to test efficiency of quantum particle swarm optimization relevance feedback algorithm based on weight adjustment QPSOWA, we do another experiment. $\alpha = 0.1$, $\beta = 0.6$, $\gamma = 0.3$ and the number of result is 12. Take busses for example, after four rounds of feedback retrieval results of algorithm based on learning weighted distances for relevance feedback is shown in Fig. 3 and retrieval results of our proposed algorithm is shown in Fig. 4. Accuracy comparison of different algorithms is shown in TABLEIII and average feedback accuracy of different categories of image in five round of feedback is shown in TABLEIV. It can be seen from TABLEIII data, initial accuracy of QPSOWA before feedback is only 0.097, but after the first round of feedback, the improvement amplitude of retrieval precision of QPSOWA is much higher than other methods, and the precision after each round of feedback are superior to other methods.

TABLE III.
ACCURACY COMPARISON OF DIFFERENT ALGORITHM

round	Bayesian[21]	Content-based[22]	Learning weighted distances[23]	QPSO WA
round0	-	0.222	0.115	0.097
round1	0.520	0.467	0.422	0.775
round2	0.660	0.598	0.641	0.855
round3	0.710	0.693	-	0.860

TABLE IV.
AVERAGE FEEDBACK ACCURACY OF DIFFERENT CATEGORIES OF IMAGE IN FIVE ROUNDS

category	round1	round2	round3	round4	round5
africa	0.648	0.644	0.660	0.600	0.620
beaches	0.360	0.356	0.396	0.408	0.392
monuments	0.292	0.332	0.334	0.348	0.340
busses	0.712	0.832	0.828	0.840	0.852
dinosaurs	0.996	1	1	1	1
elephants	0.444	0.462	0.480	0.484	0.480
flowers	0.544	0.728	0.754	0.756	0.806
horses	0.864	0.864	0.872	0.896	0.896
mountain	0.280	0.344	0.312	0.356	0.370
cookie/food	0.632	0.676	0.708	0.676	0.718
average	0.5772	0.6238	0.6344	0.6364	0.6474

It can be seen from TABLEIV, with the increasing of number of feedback round, the retrieval accuracy is gradually improved, which shows that automatic evolution search process of QPSO can combine with user feedback cognition efficiently and can search image library completely to meet user requirements. In the first round, average accuracy of QPSOWA is 0.5772, in the second round, average accuracy of QPSOWA is 0.6238, in the third round, average accuracy of QPSOWA is 0.6344, in the fourth round, average accuracy of QPSOWA is 0.6364 and in the fifth round, average accuracy of QPSOWA is 0.6474.

In the feedback process, since specificity of each feedback result and content of some images are chaos, so it can make retrieval accuracy fluctuate within a certain range. But it has no effect on the increasing trend of the average retrieval accuracy, and the overall average retrieval precision converges to more than 0.6 after repeated feedback. Proposed algorithm QPSOWA has good effect.

Figure3. Retrieval results of algorithm based on learning weighted distances for relevance feedback

Figure4. Retrieval results of our proposed algorithm

V. CONCLUSIONS

Weighted coefficients of image retrieval algorithm based on relevance feedback are determined in advance, which is lack of flexibility. In CBIR, there are many problems. Training samples are few, real-time requirement is high, training samples is asymmetric, large quantity samples are not marked, and re-weighting is inflexible. Quantum particle swarm optimization algorithm is introduced into relevance feedback. QPSO relevance feedback algorithm based on image coding(QPSO-IE) and quantum particle swarm optimization relevance feedback algorithm based on weight adjustment(QPSOWA) are proposed. QPSO-IE proposes effective solutions for the key points of coding, space continuity, constraint condition, evaluation criterion, and terminal condition. QPSOWA algorithm is made up of user feedback process and particle evolution process. When feedback is required, the particle swarm is initialized firstly, then user selects relevant images as feedback results. The direction of particles evolution is supervised by individual average value as current global best position. In particle evolution process, the speed and position of particles are adjusted according to fitness, and discrete image points are determined as the discrete solution of relevance feedback after current round. QPSOWA algorithm aims at the inflexible weight adjustment problem of RF, combines with quantum particle swarm optimization, and has fast convergence speed. Weights are adjusted to optimal value among wide particle search space, which achieves good retrieval effect.

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