A Relevance Feedback Approach Based on Modification of Similarity Measure Using Particle Swarm Optimization in a Medical X-ray Image Retrieval System

Hossein Pourghassem
Department of Electrical Engineering, Islamic Azad University, Najafabad Branch (IAUN), Iran
Email: h_pourghasem@iaun.ac.ir

Received: November 2009 Revised: January 2010 Accepted: April 2010

ABSTRACT:
Relevance feedback (RF) approaches have been used to improve the performance of content-based image retrieval (CBIR) systems. In this paper, an RF approach based on modification of similarity measure using particle swarm optimization (PSO) in a medical X-ray image retrieval system is proposed. In this algorithm, using PSO, the significance of each feature in the similarity measure is modified for image retrieval. This modification causes that good features have major effect in relevant image retrieval. The defined fitness function in PSO uses relevant and irrelevant retrieved images with different strategies, simultaneously. The relevant and irrelevant images are used to exhort and penalize similarity measure, respectively. The proposed RF is integrated to a CBIR system based on semantic classification for evaluation. In this system, using merging scheme in a hierarchical structure, the overlapped classes are merged together and determined search space for each query image. The proposed RF evaluated on a database consisting of 10000 medical X-ray images of 57 classes. The proposed algorithm provides the improvement, effectiveness more than those reported before.

KEYWORDS: Relevance Feedback, Particle Swarm Optimization, Content-Based Image Retrieval, Similarity Measure, X-ray image.

1. INTRODUCTION

Having tremendous increase in medical databases and health database management, computer-aided diagnosis, medical research, education and training applications, the need for content-based search and retrieval systems is unavoidable. Traditional image retrieval approaches are divided to two categories. The first category is text-based image retrieval that textual features such as filenames and keywords have been used to annotate and retrieve relevant images. As they are applied to a large database, the use of keywords has several disadvantages. First, annotating process of images is not only time-consuming, but also a subjective task due to human perception. Second, keywords are inadequate to represent the image content and used only in one language. The second category is content-based image retrieval in the method accessing images according to their content, low-level features such as colors, textures, and shapes of objects is widely used as indexing features for image retrieval [1].

Although CBIR has widely been used in general applications (such as digital libraries, face matching for identification and law enforcement, on-line shopping, trademark searching, Internet publishing and searching, fingerprint identification), but only a few CBIR systems (such as ASSERT [2], IRMA [3], NHANES [4]) have been developed specifically in medical applications. Many medical CBIR systems such as high-resolution computed tomography (HRCT) lung images [5], mammography [6], chest CT [7], chest X-ray [8], spine X-ray [4], [9], and dental X-ray [10] often present to images with specific organ and modality or diagnostic study, and cannot be usually used for other medical applications [11]-[14]. A few systems have been developed to general medical application (e.g., KmED [15] and IRMA [3]).

In CBIR systems, there is an interaction between system and user that is called RF. RF approaches is used to improve the performance of CBIR systems. There are two main reasons for using the RF approaches in CBIR systems, semantic gap and varied human perception for each person. In image retrieval, system presents images to user that their feature vectors are neighbor to feature vector of query image in feature space, while these images are not similar to query image semantically. In other words, there is a semantic distance between low-level visual features and high-level semantic content of images that is called semantic

Archive of SID

www.SID.ir

gap. To overcome these two problems, RF approaches are applied until CBIR systems satisfy user opinion [16].

The most RF approaches are formed based on two strategies, query-point moving and weight updating. The query-point moving approach tries to improve the estimate (in terms of low level features) of the ideal query point by moving the current query point [17]-[23]. The weight updating approach is a refinement method based on modifying the weights or parameters used in the computation of similarity measure based on the user's feedback [24]-[31]. In addition, synthetic research works have been carried out based on two above approaches [32], [33].

RF approaches use either relevant (positive) images only or relevant and irrelevant (negative) images simultaneously. For example, in [19] relevant and irrelevant images are used simultaneously and in [32] relevant images are used only. In [19], positive images are used to estimate a Gaussian distribution that represents the desired images for a given query, while the negative images are used to modify the ranking of the retrieved candidates. Positive images update parameters of Gaussian distribution. Then a Bayesian classifier is applied to rank images of database. In [32], an RF framework to take advantage of the semantic contents of images in addition to low-level features has proposed. In this paper, by forming a semantic network on top of the keyword association on the images, CBIR system is able to accurately deduce and utilize the images' semantic contents for retrieval purposes. Ultimately, a suitable ranking measure is presented for this framework. In [22], a RF approach based on query expansion has been presented. In this algorithm, according to the user's RF, the proposed query expansion method calculates the degrees of importance of relevant terms of documents in the document database. This method uses fuzzy rules to infer the weights of the additional query terms. Then, the weights of the additional query terms and the weights of the original query terms are used to form the new query vector.

In this paper, an RF approach based on modification of similarity measure using particle swarm optimization in a medical X-ray image retrieval system is presented. In this approach, the degree of importance of each image feature in forming of similarity measure is modified to image retrieval; note that we use PSO algorithm. Until in the next retrieval, good features (features with more degree of importance) have major effect in relevant image retrieval. The defined fitness function in PSO algorithm uses relevant and irrelevant retrieved images with different strategies, simultaneously. The relevant and irrelevant images are used to exhort and penalize similarity measure, respectively. The measure of persuasion or punishment is weighted Euclidean distance between query image and database images. The proposed RF is integrated to a CBIR system based on semantic classification. In this system, using merging scheme in a hierarchical structure, the overlapped classes are merged together and determined search space for each query image. In this system, semantic classifier uses a perfect set of shape and texture features and two features, tessellation-based spectral and directional histogram features [34], [36].

This paper is organized as follows. Section 2 describes details of the proposed RF. Section 3 introduces image retrieval system that the proposed RF is integrated it on. Experimental results are shown in Section 4. Finally, Section 5 gives a conclusion to the work and comparison with other works.

2. THE PROPOSED RELEVANCE FEEDBACK

In this paper, an RF approach based on PSO algorithm in medical X-ray image retrieval system is presented. Positive and negative images are used to modify similarity measure of the proposed RF approach. The proposed RF has designed

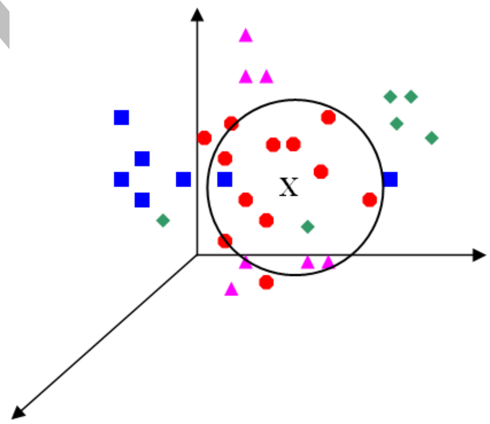


Fig. 1. Feature space and positive and negative images around query image.

Based on persuasion and punishment of similarity measure by weighted Euclidean distance retrieved images and query image in the feature space. We consider 3-dimensional feature space, shown in figure1, for these features. In this Figure, query image has represented by symbol x and database images of different classes are shown by symbols ●, ◆, ▲ and ■. Drawn circle on the feature space in Figure 1 determines search space of the query image x. Retrieved images are consisting of positive images (8 images with symbol ●) and negative images (one image with symbol ■, one image with symbol ◆ and two images with symbol ▲) that shown in the feature space. In the proposed RF, the close images to query image have more effect in the similarity measure. In the following, details of the proposed RF are described.

Archive of SID
www.SID.ir

2.1. Particle Swarm Optimization

The PSO algorithm is an optimization approach based on the social behavior of collection of animals such as birds and fishes [37]. In this algorithm, each individual of the swarm, called particle, remembers the best solution found by itself and by the whole swarm along the search trajectory. The particles move along the search space and exchange information with other particles.

X denote the current position in the search space, and V is the current velocity. During each iteration, each particle in the swarm is updated using the following equations

$$V(t+1) = \omega V(t) + c_1 r_1 (pBest(t) - x(t)) + c_2 r_2 (pBest(t) - x(t)) \quad (1)$$

$$x(t+1) = x(t) + V(t+1) \quad (2)$$

where r_1 and r_2 are the element from uniform random sequence in the range [0,1], and c_1 and c_2 are the acceleration coefficients, usually $c_1 = c_2 = 2$. ω is the weight coefficient and $0.1 \le \omega \le 0.9$ [37]. *p*Best, the personal best position of each particle, is updated by

$$pBest(t+1) = \begin{cases} pBest & if\ f(x(t+1)) \le f(pBest(t)) \\ x(t+1) & if\ f(x(t+1)) > f(pBest(t)) \end{cases} \quad (3)$$

and *g*Best, the global best position, is the best position among all particles in the swarm during all previous steps. It means

$$gBest(t+1) = \arg\max_i f(pBest_i(t+1)) \quad for\ any\ particle\ i. \quad (4)$$

The value of *V* can be clamped to the range $[-V_{\max}, V_{\min}]$ to ensure particles in the search space. The variable ω is the inertia weight, this means that the value of ω is typically setup to vary linearly from maximum to minimum during the course of iterations, and ω is formulated as follows:

$$\omega = \omega_{\max} - iter \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}}, \quad (5)$$

Where $iter_{\max}$ is the time of maximum iteration, and $iter$ is the time of current iteration.

In the course of searching by using PSO, if a particle discovers a current optimal position (not global optimal point), all the other particles will move closer to it, then particles are in the dilemma of local optimal point. This is so-called premature convergence.

2.2. Fitness Function and Similarity Measure

In optimization procedure based on PSO algorithm, important problem is determination of optimum position in the PSO consecutive iterations. It is accomplished with fitness function. In this paper, fitness function is designed based on persuasion of positive images and punishment of negative images. The value of fitness function $f(x(t))$ for each position $x(t)$ and each stage of retrieval is defined as,

$$f(x(t)) = \sum_{I \in positive\ images} P_I - \sum_{I \in negative\ images} N_I \quad (6)$$

Where P_I and N_I are the persuasion value of positive images and the punishment value of negative images in the retrieved images, respectively. They are defined as

$$P_I = \exp(1 - \frac{D(I,q) - D_{\min}}{D_{\max} - D_{\min}}) \quad for\ I \in positive\ images, \quad (7)$$

$$N_I = \exp(1 - \frac{D(I,q) - D_{\min}}{D_{\max} - D_{\min}}) \quad for\ I \in negative\ images, \quad (8)$$

Where $D_{\min}$ and $D_{\max}$ are the minimum and maximum values of distance query image and retrieved images, respectively. $D(I,q)$ is weighted Euclidean distance of image I and image q, that is defined as

$$D(I,q) = \sqrt{\sum_{i=1}^{d} x_t(i)(I(i) - q(i))^2} \quad (9)$$

Where d is feature vector dimension and x_t is position vector of each particle in time t.

3. CONTENT-BASED IMAGE RETRIEVAL FRAMEWORK

CBIR Framework is based on image semantic classification. In this framework, a hierarchical structure and a merging scheme for overlapped classes are used to improve the classification performance. Block diagram of CBIR framework is shown in figure. 2.

In this block diagram, shape and texture features are extracted from query image, and then *m*-nearest classes to the query image are determined by the semantic classifier. Similar images in the search space are sorted by similarity measure and presented to user. Positive and negative images in the presented images are labeled by user, and then used to improve the retrieval performance by a RF algorithm. In the following, more details of this framework are described.

3.1. Feature Extraction

In the used retrieval framework, a rich set of shape, edge and texture features is used to classify and retrieve X-ray images. We extract shape features such as Fourier descriptor [38], major axis orientation, eccentricity, major and minor axis length [39], moment invariants [40], texture features such as contrast,

Archive of SID

www.SID.ir

homogeneity, energy and correlation [41] and directional histogram and tessellation-based spectral features [34], [36].

3.2. Semantic Classification and Retrieval

A semantic classification will greatly enhance the performance of CBIR systems by filtering out the images of irrelevant classes and reducing the search space. Therefore, image classification is an important stage in a CBIR system. In the used CBIR framework, to increase the classification performance, and create homogeneous classes based on body orientation, anatomic region and texture contents, we use an algorithm to merge

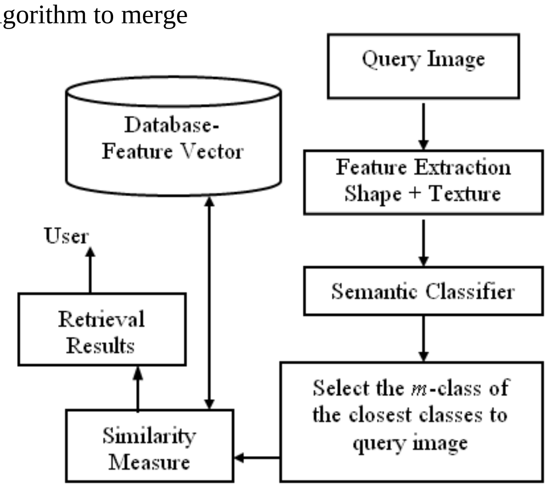


Fig. 2. Block diagram of the proposed CBIR system.

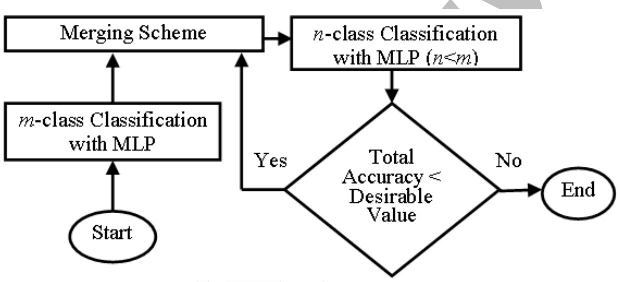


Fig. 3. Block diagram of the merging scheme [34].

Overlapped classes that is called merging scheme [34]. Applying the merging scheme on classification results, homogeneous classes are formed. Ultimately, for each query image, semantic classifier determines *m*-nearest classes to the query image as search space.

3.2.1. Merging Scheme

Pourshassem and Ghassemian provided the merging scheme for merging overlapped classes [34], is presented. The merging scheme is an iterative procedure, i.e., classes with maximum overlap are merged, and MLP classifier is then retrained based on new merged classes and evaluated on test dataset. If the total accuracy of new classification problem is lower than desirable value ($T_{desired}$), merging process will be carried out in the next iteration, otherwise it is stopped. Figure 3 shows the iterative process of the merging scheme.

To detect the overlapping classes, three measures are applied. First, the accuracy rate of the overlapping classes that is called accuracy measure. Second, miss-classified ratio (M_{ij}) between class i and class j is defined as below:

$$M_{ij} = \frac{\#\ images\ of\ class\ i\ that\ is\ classified\ to\ class\ j}{\#\ images\ of\ the\ assigned\ images\ to\ class\ i\ and\ class\ j} \quad (10)$$

for each class i
  if ($accuracy$ measure $< \alpha$)
    for each class $j \neq i$
      if ($M_{ij} > \beta$)
        if ($D(f_i \| f_j) < \gamma$)
          To merge class i and class j and break loop.
        end
      end
    end
  end
end

Fig. 4. Merging scheme in an iteration [34].

Thirdly, the correlation distance between two distribution functions of class i and class j ($D(f_i \| f_j)$), dissimilarity measure, is applied. Merging scheme is shown in figure 4, in details.

4. EXPERIMENTAL RESULTS

The database used in this research is a collection of 10000 images consisting of 57 different radiological X-ray classes (image sample of each class are shown in figure 5). The images are database of the IRMA project X-ray library (IMAGECLEF 2005) [42], which is being collected and labeled by experts. All images were downscaled to fit into a (512×128 up to 512×512 pixels, 8 bits) bounding box maintaining the original aspect ratio. This database has been divided into two training (9000 images) and test (1000 images) datasets. The proposed algorithm is implemented in Matlab 7.1 software on a PC equipped with 2GHz dual core CPU and 1GHz RAM.

4.1. Evaluation Parameters of Image Retrieval

This paper, we use the standard measures such as precision and recall to evaluate the result. These parameters are defined as below:

$$\mathrm{Re}\,call = \frac{Number\ of\ images\ retrieved\ and\ relevant}{Total\ number\ of\ relevent\ images\ in\ the\ database} \quad (11)$$

Archive of SID

www.SID.ir

$$\Pr ecision = \frac{Number\ of\ images\ retrieved\ and\ relevant}{Total\ number\ of\ retrieved\ images} \quad (12)$$

Moreover, P(R=0.5), the precision at the point where recall is 0.5; P(R=P), the precision where recall and precision are equal; P(N_R), the precision after N_R images retrieved; are used in the evaluation of the previous presented systems [43].

Fig. 5. Image sample of 57-class database.

4.2. Semantic Classification Based on Merging Scheme

The merging-based classifier groups query images based on the extracted features (figure 2). According to block diagram of figure 3, images are classified into 57 classes with multilayer perception classifier that accuracy rate 58.27% is obtained. In the merging scheme, accuracy rate (α), misclassified ratio (β) and dissimilarity (γ) thresholds and the desired value of the total classification accuracy rate are set to 60%, 0.3, 0.75 and 90%, respectively. The results of applying the merging scheme in the tertiary iteration are obtained in Table 1. In Table 1, database classes is shown only with class index while new classes (merged classes) shown with letter C.

After applying the first iteration of the merging scheme, the number of classes is decreased to 28 classes but the total classification accuracy rate is increased to 84.6%. Because, the total accuracy rate is lower than desired value ($T_{desired}$ =90%), therefore, the second iteration of the merging scheme is executed. After applying the second iteration of the merging scheme, the total classification accuracy rate is improved to 88.1% for a 22-class classification problem. Therefore, algorithm iterates for the tertiary iteration. The total classification accuracy rate is increased to 90.9% for a 19-class classification problem. In this iteration, the desired value of the total accuracy rate has obtained, so the merging scheme is terminated.

4.3. Feature Space Selection and Image Retrieval

According to block diagram of figure 2, using semantic classification based on merging scheme, search space is determined with *m*-nearest classes to the query image as search space. We set *m* to 5 until this value guarantees the existence of relevant images in 98.88% of query images. The classification results for different values of *m* are shown in Table 2.

Table 1. The results of applying the merging scheme in the tertiary iteration

Merged class	Class name	Accuracy rate (%)
C1	1, 43, 45	96.11
C2	3	93.33
C3	4	92
C4	5	96.77
C5	6, 7, 8, 9, 18, 19, 20, 24, 28, 29, 31, 32, 35, 36, 37, 47	90
C6	10, 14, 15, 23, 26, 34, 46, 51	88.6
C7	2, 11, 12, 13, 16, 17, 33, 40, 44	98.8
C8	21, 22, 30, 38, 39	89
C9	25	90.91
C10	27, 53	78.36
C11	41	91.9
C12	42	90
C13	48	96
C14	49	95
C15	50	76.77
C16	52	95
C17	54, 56	91
C18	55	89.8
C19	57	98.25

Table 2. Classification results in m-class of the closest classes to query image.

m-class of the closest classes	Accuracy rate (%)
1	90.09
2	94.88
3	96.21
4	98.13
5	98.88
6	99.22

Archive of SID

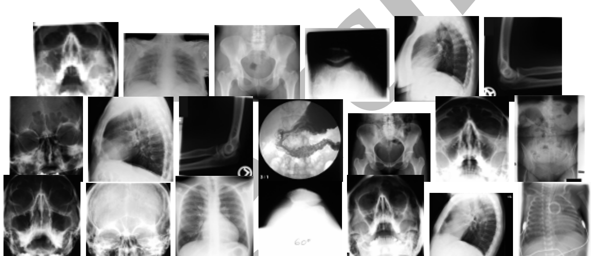
www.SID.ir

4.4. Interactive Retrieval with the proposed RF

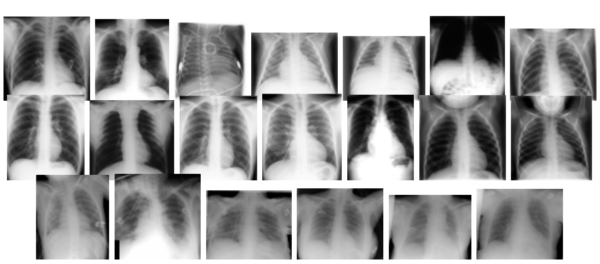
To improve the performance of retrieval, the proposed RF is used. The proposed RF uses the positive and negative images to calculate fitness value of PSO algorithm. Then PSO modifies similarity measure based on weight of each feature.

For example, figure 6 shows retrieval results without RF and the first three iterations of RF for a query image (figure 6.a). Figure 6.b shows the first twenty retrieved images without RF. User determines the positive and negative images and returns them to system. figure 6.c shows the first twenty retrieved images in the first RF. The number of the positive image is increased in the first RF. If the proposed RF recurs to the second and tertiary iteration, again, the number of the positive images is increased. figure 6.d and 6.e show the first twenty retrieved images in the second and tertiary RF, respectively. figure 7 presents the precision versus recall curves of the first three iterations of RF for shown retrievals in figure 6. In figure 7, the precision versus recall curves show that the considerable improvement is obtained from retrieval without RF to the first iteration of RF (curve with symbol ○ versus curve with symbol ×) whereas these improvements in the next iterations are sensible. figure 8 and 9 show precision and recall curves for figure 6, respectively. The results of the proposed RF on test dataset are obtained in Table 3.

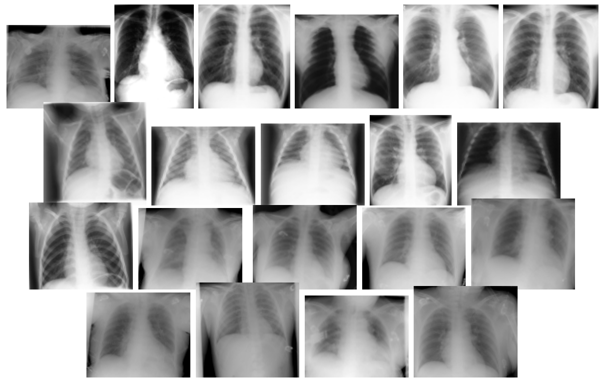
(a) Query image



(b) Retrieved images without RF

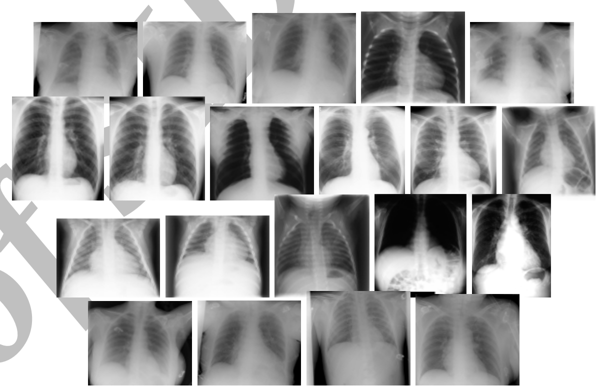


(c) Retrieved images in the first iteration of RF



(d) Retrieved images in the second iteration of RF

(e)



(f) Retrieved images in the tertiary iteration of RF

Fig. 6. Retrieval results a query image without RF and the first three iterations of RF (all images are sorted from up to down and left to right).

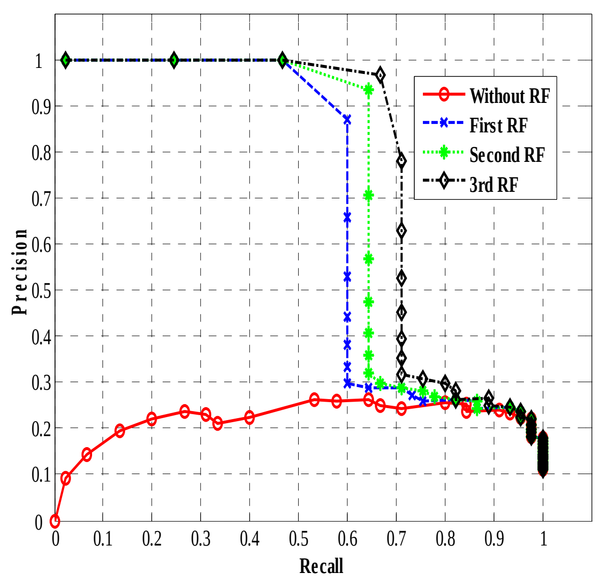


Fig. 7. Precision versus recall curves of the query image retrievals in Figure 6.

Archive of SID

www.SID.ir

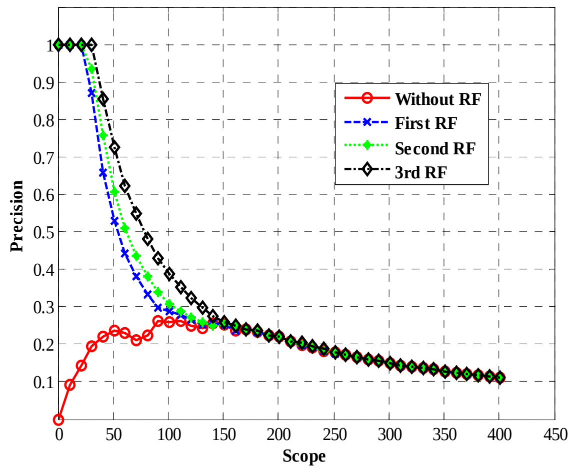


Fig. 8. Precision curves of the query image retrievals in Figure 6.

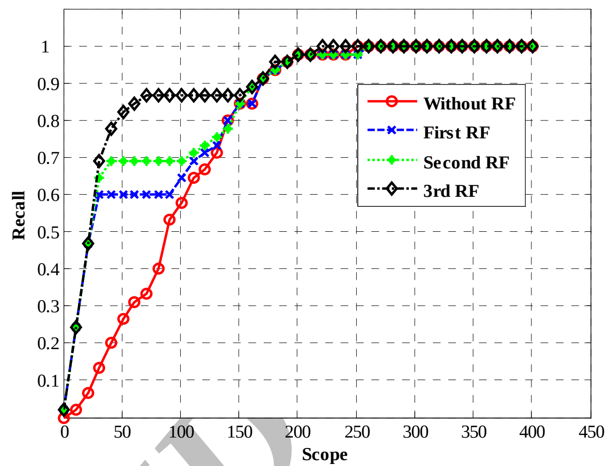


Fig. 9. Recall curves of the query image retrievals in Figure 6.

Table 3. The results of the proposed RF on test dataset.

Retrieval stages	Evaluation measures		
	P(R=P)	P(20)	P(R=0.5)
Without RF	0.38	0.48	0.33
First RF	0.5	0.84	0.72
Second RF	0.56	0.85	0.76
Tertiary RF	0.63	0.86	0.79

Table 4. Comparison between the proposed RF and the previous works.

Approach	Database	Retrieval measures	
		P(R=P)	P(R=0.5)
Alg. [11] (without RF)	1501 images of 17 classes (ImageCLEFmed 2005)	0.62	0.67
Alg. [12] (with RF)	5000 images of 20 classes (ImageCLEFmed 2004)	0.68	0.82
Alg. [13] (with RF)	11000 images of 116 classes (ImageCLEFmed 2006)	0.61	0.64
Proposed alg. (without RF)	10000 images of 57 classes (ImageCLEFmed 2005)	0.38	0.33
Proposed alg. (first RF)	10000 images of 57 classes (ImageCLEFmed 2005)	0.50	0.72
Proposed alg. (second RF)	10000 images of 57 classes (ImageCLEFmed 2005)	0.56	0.76
Proposed alg. (tertiary RF)	10000 images of 57 classes (ImageCLEFmed 2005)	0.63	0.79

5. CONCLUSION AND COMPARISON

In this paper, an RF approach based on modification of similarity measure using PSO in a medical X-ray image retrieval system is presented. In this approach, using PSO algorithm, the degree of importance of each image feature in forming of similarity measure is modified to image retrieval. Until in the next retrievals, good features (features with more degree of importance) have major effect in relevant image retrieval. The defined fitness function in PSO algorithm uses relevant and irrelevant retrieved images with different strategies, simultaneously. The relevant and irrelevant images are used to exhort and penalize similarity measure, respectively. To evaluate the proposed RF, it is integrated to a CBIR system based on semantic classification. In this system, using merging scheme in a hierarchical structure, the overlapped classes are merged together and determined search space for each query image. The proposed RF evaluated on a database consisting of 10000 medical X-ray images of 57 classes.

An exact comparison across the presented algorithms in the literature is a complex task because type and the number of images and classes of database

Archive of SID

www.SID.ir

are very important parameters in evaluation of the performance. In this paper, we compare our proposed RF to works with the same database. Table 4 obtains comparison between the proposed RF and the previous works. In Table 4, the reported results are weaker to our work except algorithm [12]. This algorithm has evaluated on a database consisting of 5000 images of 20 predefined classes. Whereas our database is twice as the number of images, therefore the performance of the proposed RF is rather satisfactory. The presented algorithm in [13] has evaluated on database consisting of 11000 images, however our algorithm has considerable improvement based on P(R=0.5) measure. The best reported retrieval result in [11] on a dataset of 1501 radiological images of 17 classes was 0.67 and 0.62 for P(R=0.5) and P(R=P), respectively. Extending the presented GMM-KL framework in [11] to work on such a large dataset is a challenge, especially due to the computational load involved with the KL measure. Whereas, this extension to a larger database in our proposed CBIR framework is not a challenge. Our results demonstrate the effectiveness of the proposed algorithm as compared with other state-of-the-art RF techniques.

6. ACKNOWLEDGMENT

This work was supported by Islamic Azad University Najafabad Branch (IAUN) based on approved research proposal.

REFERENCES

[1] Liu Y., Zhang D., Lu G. and Ma W.Y.; **"A Survey of Content-based Image Retrieval with High-level Semantics"**, *Pattern Recognition*, Vol. 40, pp. 262-282, (2007)

[2] Shyu C., Brodley C., Kak A., Kosaka A., Aisen A. and Broderick L.; **"Assert: a Physician-in-the-loop Content-Based Image Retrieval System for Hrct Image Databases"**, *Computer Vis. and Image Under*., Vol. 75, No. 1, pp. 111-132, (1999)

[3] Lehmann T., Guld M., Thies C., Fischer B., Spitzer K., Keysers D., Ney H., Kohnen M., Schubert H. and Wein B.; "**Content-based Image Retrieval in Medical Applications"**, *Methods Inform. Med*., Vol. 43, No. 4, pp. 354-361, (2004)

[4] Antani S., Lee D.J., Long L.R. and Thoma G.R.; **"Evaluation of Shape Similarity Measurement Methods for Spine X-ray Images"**, *J. of Vis. Comm. and Image R*ep., Vol. 15, No. 3, pp. 285-302, (2004)

[5] Dy J.G., Brodley C.E., Kak A., Broderick L.S. and Aisen A.M.; **"Unsupervised Feature Selection Applied to Content-based Retrieval of Lung Images"**, *IEEE Trans. Pattern Anal. Mach. Intell*., Vol. 25, No. 3, pp. 37–378, (2003)

[6] Korn P., Sidiropoulos N., Faloutsos C., Siegel E. and Protopapas Z.; **"Fast and Effective Retrieval of Medical Tumor Shapes"**, *IEEE Trans. Knowl. Data Eng*., Vol. 10, No. 6, pp. 889-904, (1998)

[7] Yu S.N., Chianga C.T. and Hsieh C.C.; **"A Three-object Model for the Similarity Searches of Chest Ct Images"**, *Computerized Medical Imaging and Graphics*, Vol. 29, pp. 617-630, (2005)

[8] Oliveira L.L.G., Silva S.A., Ribeiro L.H.V., Oliveira R.M., Coelho C. and Andrade A.S.S.; **"Computer-aided Diagnosis in Chest Radiography for Detection of Childhood Pneumonia"**, *Int. J. Med. Inform*., Vol. 77, No. 8, pp. 555-564, (2007)

[9] Xu X., Lee D.J., Antani S. and Long L.R., **"A Spine X-ray Image Retrieval System Using Partial Shape Matching"**, *IEEE Trans. on Information Technology in Biomedicine*, Vol. 12, No. 1, pp. 100-108, (2008)

[10] Nomira O. and Abdel-Mottalebb M.; **"Hierarchical Contour Matching for Dental X-ray Radiographs"**, *Pattern Recognition*, Vol. 41, pp. 130-138, (2008)

[11] Greenspan H. and Pinhas A.T., **"Medical Image Categorization and Retrieval for Pacs Using the Gmm-Kl Framework"**, *IEEE Trans. on Information Technology in Biomedicine*, Vol. 11, No. 2, pp. 190-202, (2007)

[12] Rahman M.M., Bhattacharya P. and Desai B.C.; **"A Framework for Medical Image Retrieval Using Machine Learning and Statistical Similarity Matching Techniques with Relevance Feedback"**, *IEEE Trans. on Inf. Tech. in Bio*., Vol. 11, No. 1, pp. 58-69, (2007)

[13] Rahman M.M., Desai B.C. and Bhattacharya P., **"Medical Image Retrieval with Probabilistic Multi-class Support Vector Machine Classifiers and Adaptive Similarity Fusion"**, *Computerized Medical Imaging and Graphics*, Vol. 32, pp. 95-108, (2008)

[14] Yao J., Antani Z.S., Long R. and Thoma G., **"Automatic Medical Image Annotation and Retrieval"**, *Neurocomputing*, Vol. 71, No. 10, pp. 2012-2022, (2008)

[15] Chu W.W., Hsu C.C., Cardenas A.F. and Taira R.K.; **"Knowledge-based Image Retrieval with Spatial and Temporal Constructs"**, *IEEE Trans. Knowl. Data Eng*., Vol. 10, No. 6, pp. 872-888, (1998)

[16] Pourghassem H. and Ghassemian H.; **"A Novel Hybrid Relevance Feedback Based on Euclidean Distance and Probability Function Similarity Measures in a X-ray Medical Images Retrieval System"**, *Proceeding of 16th Iranian Conference on Electrical Engineering, ICEE2008*, Vol.1, pp. 197-202, (May 2008)

[17] Cox I.J., Miller M.L., Minka T.P., Papathomas T. and Yianilos P.N., **"The Bayesian Image Retrieval System, Pichunter: Theory, Implementation, and Psychophysical Experiments"**, *IEEE Trans. on Image Processing*, Vol. 9, No. 1, pp. 20-37, (Jan. 2000)

[18] El-Naqa, Yang Y., Galatsanos N.P., Nishikawa R.M. and Wernick M.N.; **"A Similarity Learning Approach to Content-based Image Retrieval: Application to Digital Mammography"**, *IEEE Transactions on Medical Imaging*, Vol.23, No.10, pp.1233-1244, (2004)

[19] Su Z., Zhang H., Li S. and Ma S., **"Relevance Feedback in Content Based Image Retrieval Bayesian Framework Feature Subspaces, and Progressive Learning"**, *IEEE Trans. on Image Processing*, Vol. 12, No. 8, pp. 924-937, (2003)

Archive of SID

www.SID.ir

[20] Ves E.d., Domingo J., Ayala G. and Zuccarello P.; **"A Novel Bayesian Framework for Relevance Feedback in Image Content-based Retrieval Systems"**, *Pattern Recognition*, Vol. 39, pp. 1622-1632, (2006) Zuccarello

[21] Efron M.; **"Query Expansion and Dimensionality Reduction: Notions of Optimality in Rocchio Relevance Feedback and Latent Semantic Indexing"**, *Information Processing and Management*, Vol. 44, pp. 163–180, (2008)

[22] Lin H-C, Wang L-H and Chen S-M: **"Query Expansion for Document Retrieval Based On Fuzzy Rules and User Relevance Feedback Techniques"**, *Expert Systems with Applications*, Vol. 31, pp. 397–405, (2006)

[23] Wong W.S., Luk R.W.P., Leong H.V., Ho K.S. and Lee D.L.; **"Re-examining the Effects of Adding Relevance Information in a Relevance Feedback Environment"**, Information Processing and Management, Vol. 44, No. 3, pp. 1086-1116, (May 2008)

[24] Wu Y. and Zhang A., **"A Feature Re-weighting Approach for Relevance Feedback in Image Retrieval"**, in *Proc. of IEEE Int. Conf. on Image (ICIP02)*, Rochester, New York, (September 2002)

[25] Carneiro G., Chan A.B., Moreno P.J. and Vasconcelos N.; **"Supervised Learning of Semantic Classes for Image Annotation and Retrieval"**, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 29, No. 3, pp. 394-410, (2007)

[26] Yoo H-W; **"Retrieval of Movie Scenes by Semantic Matrix and Automatic Feature Weight Update"**, *Expert Systems with Applications*, Vol. 34, pp. 2382–2395, (2008)

[27] Kim D-H and Yu S-H; **"A New Region Filtering and Region Weighting Approach to Relevance Feedback in Content-based Image Retrieval"**, *The Journal of Systems and Software*, Vol. 81, No. 9, pp. 1525-1538, (September 2008)

[28] Rooney N., Patterson D., Galushka M. and Dobrynin V.; **"A Relevance Feedback Mechanism for Cluster-based Retrieval"**, *Information Processing and Management*, Vol. 42, pp. 1176-1184, (2006)

[29] Cheng P-C, Chien B-C, Ke H-R and Yang W.P., **"A Two-level Relevance Feedback Mechanism for Image Retrieval"**, *Expert Systems with Applications*, Vol. 34, pp. 2193–2200, (2008)

[30] Saha S.K., Das A.K. and Chanda B.; **"Image Retrieval Based on Indexing and Relevance Feedback"**, *Pattern Recognition Letters*, Vol. 28, pp. 357–366, (2007)

[31] Qin T., Zhang X.D., Liu T.Y., Wang D.S., Mab W.Y. and Zhang H.J., **"An Active Feedback Framework for Image Retrieval",** *Pattern Recognition Letters*, Vol. 29, pp. 637–646, (2008)

[32] Lu Y., Zhang H., Wenyin L. and Hu C.; **"Joint Semantics and Feature Based Image Retrieval Using Relevance Feedback"**, *IEEE Trans. on Multimedia*, Vol. 5, No. 3, pp. 339-347, (2003)

[33] Leóna T., Zuccarellob P., Ayalaa G., deVesb E. and Domingoc J.; **"Applying Logistic Regression to Relevance Feedback in Image Retrieval Systems"**, *Pattern Recognition*, Vol. 40, pp. 2621- 2632, (2007)

[34] Pourghassem H. and Ghassemian H.; **"Content-based Medical Image Classification Using a New Hierarchical Merging Scheme"**, *Journal of Computerized Medical Imaging and Graphics*, Vol. 22, No. 8, pp.651-661, (2008)

[35] Pourghassem H. and Ghassemian H.; **"Content-based Medical Classification in a Hierarchical Structure Using a New Unsupervised Clustering"**, *Proc. of the 13th Computer Society of Iran Computer Conf. (CSICC08)*, Vol. 1, pp. 78-81, (March 2008)

[36] Pourghassem H. and Ghassemian H.; **"Content-based Medical Image Classification Using Spectral Features and Directional Histogram in Multi scale Space"**, *Proc. of Int. Conf. on Biomedical Engineering (ICBME2008)*, Vol. 1, pp. 124-130, (January. 2008)

[37] Kennedy J. and Eberhart R.; **"Particle Swarm Optimization",** *Proc. of the IEEE International Conference on Neural Networks, Perth, Australia*, Vol. 4, pp. 1942–1948, (1995)

[38] Persoon E. and Fu, K. **"Shape Discrimination Using Fourier Descriptors",** IEEE *Trans Sys Man and Cybern*., Vol. 7, pp. 170-179, (1977)

[39] Jain A.K.; Fundamentals of Digital Image Processing, Prentice Hall, NJ, (1989)

[40] Yang L. and Algregtsen F., **"Fast Computation of Invariant Geometric Moments: a New Method Giving Correct Results",** *Proc. IEEE ICIP*, pp. 201-204, (1994)

[41] Haralick R.M., Shanmugan K., Dinstein I.; **"Textural Features for Image Classification"**, *IEEE Trans. on Sys. Man and Cybern*., Vol. 3, No. 6, pp. 610-621, (1973)

[42] Lehmann T., Guld M., Thies C., Fischer B., Spitzer K., Keysers D., Ney H., Kohnen M., Schubert H. and Wein B.B.; **"Content-based Image Retrieval in Medical Applications"**, *Methods Inform. Med*., Vol. 43, No. 4, pp. 354-361, (2004)

[43] Deselaers T., Keysers D. and Ney H.; **"Classification Error Rate for Quantitative Evaluation of Content-based Image Retrieval Systems"**, *Proc. of the 17th Int. Conf. on Pattern Recognition*, Vol. 2, pp. 505-508, (2004)

Archive of SID

www.SID.ir