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Segmentation of Multispectral Magnetic Resonance Image Using Penalized Fuzzy Competitive Learning Network

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Segmentation (tissue classification) of the medical images obtained from Magnetic resonance (MR) images is a primary step in most applications of computer vision to medical image analysis. This paper describes a penalized fuzzy competitive learning network designed to segment multispectral MR spin echo images. The proposed approach is a new unsupervised and winner-takes-all scheme based on a neural network using the penalized fuzzy clustering technique. Its implementation consists of the combination of a competitive learning network and penalized fuzzy clustering methods in order to make parallel implementation feasible. The penalized fuzzy competitive learning network could provide an acceptable result for medical image segmentation in parallel processing using the hardware implementation. The experimental results show that a promising solution can be obtained using the penalized fuzzy competitive learning neural network based on least squares criteria.

INTRODUCTION

In clinical diagnosis, MRI systems have become a standard tool for detecting a variety of tumors, lesions, and abnormalities. Differing from other diagnostic techniques, Magnetic resonance imaging (MRI) systems can produce several images, each of which emphasizes a different fundamental parameter of internal anatomical structures in the same body section with multiple contrasts, based on local variations of spin–spin relaxation time (T_2), spin–lattice relaxation time (T_1), and proton density (PD). This multiparametric nature of MRI provides the potential for greatly improved sensitivity and specificity in the detection of pathological conditions. In a sense the images obtained from MRI systems resemble the multispectral images of the earth (LANDSAT images) obtained from remote sensing satellites.

Manual segmentation is more difficult, time-consuming, and costly than automated processing by a computer system. Due to the low tissue contrast, the unclear tissue boundaries, and the poor hand-eye consistency, errors sometimes occur. The advantage of generating consistent results is offered by the automated procedures in MR image segmentation. The automated segmentation of MR

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images into anatomical tissues, fluids, and structures is an interesting field in medical image analysis. In clinical medicine, the use of multispectral MR images in tissue classification of normal and pathological tissue structures provides proper assistance. For instance, it can be used to differentiate various tumor types in the uterus (*1*). Several studies on the automatic recognition of normal tissues in the brain and its surrounding tissues have been proposed (*2*, *3*). In general, a quantitative strategy for the analysis of brain morphometry requires a process to segment the image into different anatomic tissue components as a main step for the determination of volume shape, and location (*4*).

Multispectral classification has been described as generating better discrimination than single spectral classification (*5*). The classical segmentation methods range from simple thresholding to more sophisticated techniques including methods based on local features such as the median, the variance, or the gradient. These techniques, however, do not take advantage of the multidimensional nature of the data (*6*). The segmentation of classification of tissues obtained from multidimensional MRIs has been successfully employed in the past (*5–13*). The analysis of such multidimensional images can be accomplished by using supervised or unsupervised classification methods. In supervised classification approaches, the region of interest (ROI) is defined by the associated human interaction and the algorithm trains on the ROI and flags each pixel in the scenes associated with a given signature. The unsupervised classification approaches classify the multidimensional data sets without the aid of training sets, but a postprocessing step is required to correct proper pixels categorized in wrong clusters.

Regarding the production of MR images, MR image signals, especially the T_2-weighted signal, are strongly dependent on both the biochemical characteristics of the tissues and the acquisition parameters. It is possible to discriminate liquid from parenchymal tissues using the T_2-weighted signal with spin echo sequences (TE). The T_2-weighted signal with different TEs has been used to distinguish healthy from pathological tissues or to classify the different tissues using supervised or unsupervised classification methods in the past (*9*, *11*).

Artificial neural networks (ANN), which have a great potential in parallel processing using hardware implementation either in a synchronous or asynchronous manner, are powerful computing systems whose architecture is made of a massive number of interconnected and nonlinear computing elements (called neurons). In the area of pattern recognition and decision making, ANNs have been established as a promising implementation of statistical, nonparametric, discriminant analysis because they can learn and synthesize the available information without requiring any statistical modeling of the problem (*14*). ANN systems possess some unique processing capabilities which are not found in conventional, sequential computing systems. An unsupervised scheme called the penalized fuzzy competitive learning network, for the classification of multidimensional T_2-weighted MR images with spin echo sequence (TE) images based on least squares criterion, is proposed to generate associated fuzzy partition of these images in this paper.

This article presents a demonstration of (i) the fuzzy clustering algorithms, (ii) the architecture between conventional competitive and penalized fuzzy competitive neural networks, and (iii) the experimental results obtained from the penalized fuzzy competitive learning neural network.

Fuzzy Clustering Techniques

Clustering is a process for classifying the objects or patterns in such a way that samples within a cluster are more similar to one another than samples belonging to different clusters. Similarity measures employed to classify samples depend on object characteristics based on distance, vector, entropy, etc. There have been many applications based on clustering paradigms. These applications include image segmentation, speech recognition, and data comparison. Many clustering strategies have been used, such as the hard clustering algorithm and the soft (fuzzy) clustering algorithm, each of which has its own special characteristics. The hard clustering algorithm, for example, c-means (*15*, *16*), will converge the objective function iteratively to a local minimum from each sample to the nearest cluster centroid. However, rather than assigning each training sample to one and only one cluster, the fuzzy clustering methods assign each training sample a degree of uncertainty described by a membership grade. A pixel's membership grade function with respect to a specific cluster indicates to what extent its properties belong to that cluster. The larger the membership grade (close to 1), the more likely that the pixel belongs to that cluster.

Fuzzy clustering strategies are mathematical tools for detecting similarities between members of a collection of samples. Since the introduction of the fuzzy set theory in 1965 by Zadeh, it has been applied in a variety of fields (*7*, *11*, *13*, *17–20*), including medical image analysis (*7*, *11*, *17*, *19*). The theory of fuzzy logic provides a mathematical framework to capture the uncertainties associated with the human cognition processes. In medical image analysis, Brandt *et al.* (*7*) proposed a fuzzy c-means approach to estimate volumes of cerebrospinal fluid (CSF), white and gray matters of the MR brain images. A fuzzy c-means clustering algorithm was applied in computerized analysis and information extraction of medical MR images by Delapaz *et al.* (*13*).

The fuzzy c-means (FCM) clustering algorithm was first introduced by Dunn (*21*), and the related formulation and algorithm was extended by Bezdek (*22*). The purpose of the FCM approach, like the conventional clustering techniques, is to minimize the criteria in the least squared error sense. For $c \geq 2$ and m any real number greater than 1, the algorithm chooses μ_i: $X \rightarrow [0, 1]$ so that $\sum_i \mu_i = 1$ and $w_j \in R^d$ for $i = 1, 2, \ldots, c$ to minimize the objective function

$$J_{FCM} = \frac{1}{2} \sum_{j=1}^{c} \sum_{i=1}^{n} (\mu_{i,j})^m \|x_i - x_j\|^2, \qquad [1]$$

where $\mu_{i,j}$ is the value of the jth membership grade on the ith sample x_i. The vectors $w_1, \ldots, w_j, \ldots, w_c$, called cluster centroids, can be regarded as prototypes for the clusters represented by the membership grades. For the purpose of minimizing the objective function, the cluster centroids and membership grades are chosen so that a high degree of membership occurs for samples close to the corresponding cluster centroids. The FCM algorithm, a well-known and powerful method in clustering analysis, is reviewed as follows.

FCM Algorithm

Step 1: Initialize the cluster centroids $w_j (2 \leq j \leq c)$, fuzzification parameter $m (1 \leq m < \infty)$, and the value $\varepsilon > 0$.

Step 2: Calculate the membership matrix $U = [\mu_{i,j}]$ using Eq. [2] as below.

$$\mu_{i,j} = \frac{\left(\frac{1}{(d_{i,j})^2}\right)^{1/(m-1)}}{\sum_{j=1}^{c}\left(\frac{1}{(d_{i,j})^2}\right)^{1/(m-1)}} \tag{2}$$

where $d_{i,j}$ is the Euclidean distance between the training sample x_i and the class centroid w_j.

Step 3: Update the class centroids

$$w_j = \frac{1}{\sum_{i=1}^{n} (\mu_{i,j})^m} \sum_{i=1}^{n} (\mu_{i,j})^m x_i \tag{3}$$

Step 4: Compute $\Delta = \max(|U^{(t+1)} - U^{(t)}|)$. If $\Delta > \varepsilon$, then go to step 2; otherwise go to step 5.

Step 5: Find the results for the final class centroids.

The value m, prechosen as any value from 1 to ∞, is called the fuzzification parameter (or exponential weight), and it reduces the noise sensitivity in the computation of the class centers. In addition, the effect for $\mu_{i,j}$ is dependent on the value m. The larger the value m ($m > 1$), the higher the dependence will be.

Another strategy of the fuzzy clustering method, called penalized fuzzy c-means (PFCM) algorithm with the addition of a penalty term, was demonstrated by Yang (*18*, *19*). It is an FCM of generalized type depending upon the penalized term in accordance with the value of w. It was shown by Yang that the PFCM algorithm is more meaningful and effective than the FCM method. The PFCM objective function is reviewed as follows:

$$\begin{aligned} J_{PFCM} &= \frac{1}{2}\sum_{j=1}^{c}\sum_{i=1}^{n} \mu_{i,j}^m \|x_i - w_j\|^2 - \frac{1}{2} v \sum_{j=1}^{c}\sum_{i=1}^{n} \mu_{i,j}^m \ln \alpha_j \\ &= J_{FCM} - \frac{1}{2} v \sum_{j=1}^{c}\sum_{i=1}^{n} \mu_{i,j}^m \ln \alpha_j, \end{aligned} \tag{4}$$

where α_j is a proportional constant of class j and $v(\geq 0)$ is a constant. When $v = 0$, J_{PFCM} equals to J_{FCM}. The penalty term, $-\frac{1}{2} v \Sigma_{j=1}^{c} \Sigma_{i=1}^{n} \mu_{i,j}^m \ln \alpha_j$, is added to the objective function and α_j, w_j, and $\mu_{i,j}$ are defined as

$$\alpha_j = \frac{\sum_{i=1}^{n} \mu_{i,j}^m}{\sum_{j=1}^{c}\sum_{i=1}^{n} \mu_{i,j}^m}; j = 1, 2, \ldots, c \qquad [5]$$

$$w_j = \frac{\sum_{i=1}^{n} \mu_{i,j}^m x_i}{\sum_{i=1}^{n} \mu_{i,j}^m}, \qquad [6]$$

which is same as the Eq. [3], and

$$\mu_{i,j} = \left(\sum_{l=1}^{c} \frac{(\|x_i - w_j\|^2 - v \ln \alpha_j)^{1/(m-1)}}{(\|x_i - w_l\|^2 - v \ln \alpha_l)^{1/(m-1)}} \right)^{-1}; i = 1, 2, \ldots, n; j = 1, 2, \ldots, c. \qquad [7]$$

Then the PFCM algorithm is presented as follows.

PFCM Algorithm

Step 1: Randomly set cluster centroids $w_j (2 \leq j \leq c)$, fuzzification parameter $m (1 \leq m < \infty)$, and the value $\varepsilon > 0$. Give a fuzzy c-partition $U^{(0)}$.

Step 2: Compute the $\alpha_j^{(t)}, w_j^{(t)}$ with $U^{(t-1)}$ using Eqs. [5] and [6]. Calculate the membership matrix $U = [\mu_{i,j}]$ with $\alpha_j^{(t)}, w_j^{(t)}$ using Eq. [7].

Step 3: Compute $\Delta = \max(|U^{(t+1)} - U^{(t)}|)$. If $\Delta > \varepsilon$, then go to step 2; otherwise go to step 4.

Step 4: Find the results for the final class centroids.

Competitive Learning Network

In the application of medical image segmentation, many schemes for the neural network have been proposed using the clustering based approach (*6*, *9*, *10*). The learning rules in neural network may be classified into the "error-based (supervised)" and "output-based (unsupervised)" algorithms (*23*). The often used competitive learning is one of the output-based learning techniques. In (*24*), Jou used a fuzzy neural network modeling and learning techniques to search for fuzzy clusters of unlabeled patterns. A fuzzy neural network model described by Yamakawa and Tomoda (*25*) was successfully applied to pattern recognition problems.

In this paper, the penalized fuzzy competitive learning is applied to the segmentation of multispectral magnetic resonance spin echo images. The structure of the neural network, shown in Fig. 1, is a two-dimensional fuzzy relation $U = [\mu_{i,j}]$ between the synaptic weights $W = \{w_1, w_w, \ldots, w_c\}$ and input samples X. It has a single layer of output neurons, each of which is fully connected to the input nodes. In order to distinguish the structure of conventional competitive and penalized fuzzy competitive learning networks, they are depicted separately as follows.

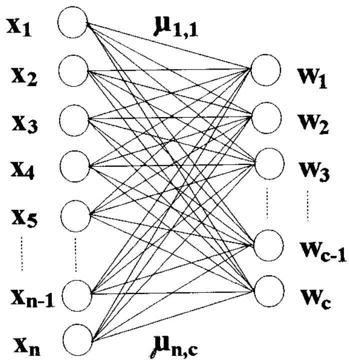

FIG. 1. The neural network topology of the proposed algorithm.

Conventional Competitive Learning Neural Network

The conventional competitive learning neural network, using the least squares error criterion and based upon Hebbian learning rules modifying the weights of the winning unit to move them closer to the input which caused it to win, has been demonstrated (*26*). Similar to the c-means clustering technique, the competitive learning would find the cluster centroids in the multidimensional pattern space. In (*26*), Uchiyama and Arbib used this network for solving the problem of color image segmentation.

Let n_j be the number of pixels in class c_j, and $w_j = \Sigma_{x_i \in c_j} x_i / n_j$ be the mean of the class c_j (i.e., the cluster centroids). Then, the scatter functions for the total (J_T), within-class (J_W), and between-class (J_B) may be defined as

$$J_T = J_W + J_B, \tag{8}$$

where

$$J_T = \frac{1}{2} \sum_{j=1}^{c} \sum_{i=1}^{n} \|x_i - w_0\|^2, \tag{9}$$

$$J_W = \frac{1}{2} \sum_{j=1}^{c} \sum_{x_i \in c_j} \|x_i - w_j\|^2, \tag{10}$$

and

$$J_B = \frac{1}{2} \sum_{j=1}^{c} \sum_{x_i \in c_j} \|w_j - w_0\|^2, \tag{11}$$

where $w_0 = \Sigma_{i=1}^{n} x_i / n$ is the global center of mass of X.

According to (*25*)and (*26*), minimization of J_w is equivalent to maximization of J_B. So, Eq. [10] could be treated as the criterion in clustering analysis. For a given class c_j, the class center w_j is representative of the samples in class c_j in the sense that it minimizes the sum of the squared error vector $x_i - w_j$. Therefore, J_w represents the measure of the least sum of squares error between n samples $x_1, x_2, \ldots, x_n$ within class and produces the c class centers $w_1, w_2, \ldots, w_c$. According to Eq. [10], the objective function for the conventional competitive learning network can be modified as

$$J_C = \frac{1}{2}\sum_{j=1}^{c}\sum_{i=1}^{n} \mu_{i,j}\,\|x_i - w_j\|^2, \qquad [12]$$

where $\mu_{i,j} = 1$ if x_i belongs to cluster c_j and $\mu_{i,j} = 0$ for all other clusters. The neuron that wins the competition is called a winner-take-all neuron. Then $\mu_{i,j}$ is used to indicate whether the input sample x_i activates neuron j to be a winner. The definition for $\mu_{i,j}$ is written as follows.

$$\mu_{i,j} = \begin{cases} 1 & \text{if } |x_i - w_j| \le |x_i - w_k|, \quad \text{for all } k; \\ 0 & \text{otherwise.} \end{cases} \qquad [13]$$

Gradient descent on the objective function [12] yields

$$\langle \Delta w_j \rangle = -\eta \frac{\partial J_c}{\partial w_j} = \eta \sum_{i=1}^{n} (x_i - w_j)\,\mu_{i,j}. \qquad [14.a]$$

Although the update rule [14.a] has been written as the sum over all samples, it is usually used incrementally, i.e., a sample is presented and then all the weights are updated before the next sample is considered. The following updated rule is usually referred to as the standard competitive learning rule:

$$\Delta w_j = \eta(x_i - w_j)\,\mu_{i,j}, \qquad [14.b]$$

which is valid for all j, and

$$w_j(t+1) = w_j(t) + \Delta w_j(t), \qquad [15]$$

where η is the learning-rate parameter. The algorithm of the conventional competitive learning is summarized as

Competitive Learning Algorithm

Step 1: Initialize the cluster centroids $w_j (2 \le j \le c)$, learning rate η, and neuron states of input samples $U = [\mu_{i,j}]$.

Step 2: Update the neuron states according to Eq. [13] with the competitive learning.

Step 3: Compute all synaptic weights (cluster centroids) according to Eqs. [14.b] and [15].

Step 4: Repeat steps 2 and 3 for all input samples, and record the number of neurons with the change state. If no neuron state is changed, then go to step 5.

Step 5: Output the final classification results.

Penalized Fuzzy Competitive Learning Neural Network

The penalized fuzzy competitive learning network has the same architecture as a conventional competitive learning network. It is an unsupervised competitive learning network using the penalized fuzzy reasoning. The objective function for this network, $J_{C,PFCM}$, is similar to that for the J_{PFCM} as

$$J_{C,PFCM} = \frac{1}{2}\sum_{j=1}^{c}\sum_{i=1}^{n}\mu_{i,j}^{m}\|x_i - w_j\|^2 - \frac{1}{2}v\sum_{j=1}^{c}\sum_{i=1}^{n}\mu_{i,j}^{m}\ln\alpha_j \qquad [16]$$

$$= J_{FCM} - \frac{1}{2}v\sum_{j=1}^{c}\sum_{i=1}^{n}\mu_{i,j}^{m}\ln\alpha_j.$$

Gradient descent on the objective function [16] yields

$$\langle\Delta w_j\rangle = -\eta\frac{\partial(J_{C,PFCM})}{\partial w_j} = -\eta\sum_{i=1}^{n}\left[\frac{\partial(J_{FCM})}{\partial w_j} - \frac{1}{2}vm(\mu_{i,j})^{m-1}(\ln\alpha_j)\frac{\partial\mu_{i,j}}{\partial w_j}\right]$$

$$= \eta\sum_{i=1}^{n}\Bigg[\mu_{i,j}^{m}(x_i - w_j) - \frac{1}{2}m(\mu_{i,j})^{m-1}\|x_i - w_j\|^2\frac{\partial\mu_{i,j}}{\partial w_j} \qquad [17]$$

$$- \frac{1}{2}vm(\mu_{i,j})^{m-1}(\ln\alpha_j)\frac{\partial\mu_{i,j}}{\partial w_j}\Bigg].$$

From Eq. [7], the derivative of $\mu_{i,j}$ with respect to w_j could be obtained as

$$\frac{\partial\mu_{i,j}}{\partial w_j} = \frac{2\mu_{i,j}(1-\mu_{i,j})(x_i - w_j)}{(m-1)(\|x_i - w_j\|^2 - v\ln\alpha_j)}. \qquad [18]$$

Replacing the $\partial\mu_{i,j}/\partial w_j$ in Eq. [17] by Eq. [18], the gradient descent on the objective function with fuzzy units can be updated as

$$\langle\Delta w_j\rangle = \eta\sum_{i=1}^{n}\mu_{i,j}^{m}(x_i - w_j)\left[1 - \frac{m}{m-1}(1-\mu_{i,j})\right]. \qquad [19.a]$$

Like the definition of the competitive learning rule and description in Eq. [14], the update rule is also written as follows:

$$\Delta w_j = \eta\mu_{i,j}^{m}(x_i - w_j)\left[1 - \frac{m}{m-1}(1-\mu_{i,j})\right]. \qquad [19.b]$$

Therefore, the PFCM algorithm with competitive learning may be described as follows.

Penalized Fuzzy Competitive Learning Algorithm

Step 1: Initialize the cluster centroids $w_j (2 \le j \le c)$, fuzzification parameter $m (1 \le m < \infty)$, learning rate η, constant v, and the value $\varepsilon > 0$. Give a fuzzy c-partition $U^{(0)}$.

Step 2: Find the $\alpha_j^{(t)}, w_j^{(t)}$ with $U^{(t-1)}$ using Eqs. [5] and [6]. Calculate the membership matrix $U = [\mu_{i,j}]$ with $\alpha_j^{(t)}, w_j^{(t)}$ using Eq. [7].

Step 3: Sequentially select a neuron to update all the weights (cluster centroids) with competitive learning according to Eqs. [15] and [19.b].

Step 4: Compute $\Delta = \max(|U^{(t+1)} - U^{(t)}|)$. If $\Delta > \varepsilon$, then go to step 2; otherwise go to step 5.

Step 5: Execute a defuzzification process and output the final classification results.

In the last step, a defuzzification process used in (*28*) is applied to the fuzzy partition data to obtain the final segmentation. A pixel is assigned to the cluster when its membership grade in that cluster is larger than 0.5. If none of its membership grades satisfy this criteria, then the class possessing the maximum grade is chosen, provided that the sum of the largest two grades is greater than 0.5 and that these two clusters are neighboring clusters in terms of distance measure. Therefore, no ambiguity in segmentation was encountered.

Experimental Results and Discussion

In order to generate the promising segmented results using the penalized fuzzy competitive learning network, the T_2-weighted MR images recorded from a man aged 32 years and formed as 256 by 256 and 8-bit gray levels with spin-echo sequences were provided. The MR images, acquired on a Siemens 1.5 Tesla Magnetom MR scanner, were 5 mm thick and 1-mm interslice space. For all the experiments, the network-associated parameters such as fuzzification parameter (m), the learning rate (η), and the constant (v), were set to be 1.5, 0.3, and 1.2, respectively. The T_2-weighted MR spin-echo images with different repetition time (TR) and echo time (TE) are shown in Figs. 2 and 3. Figures 2a–2c are acquired brain images with acquisition parameters $TR_1/TE_1 = 2500$ ms/75 ms, $TR_2/TE_2 = 2500$ ms/100 ms, and $TR_3/TE_3 = 1500$ ms/59 ms, respectively. Figures 3a–3c show the extracted peritoneal cavity images using a multiecho sequence with $TE = 130$, 144, 158 ms, $TR = 2500$ ms. Each nonzero pixel image location then consists of three gray scale values which make up what we will refer to as a "pixel vector." To begin the segmentation, an initial gray scale value representing the prototypical centroid for each cluster must be provided for each of the three images. If the initial centroid values are far from the final solution values, then more iterations will be required so as to converge to a feasible result. The segmented images, using the proposed penalized competitive learning networks, are shown in Fig. 3d in both image sets.

Due to the spectral variability in the medical image data, the task of setting constraints on the energy function for smoothing the noise is difficult. The segmented image may exhibit proper pixels categorized in wrong clusters. Such errors can be reduced by a majority filter (*29*) in postclassification filtering. Using the majority filter, a moving mask is passed over the whole segmented image. Multiple passes can be performed to control the degree of smoothness at the expense of losing some small local structures.

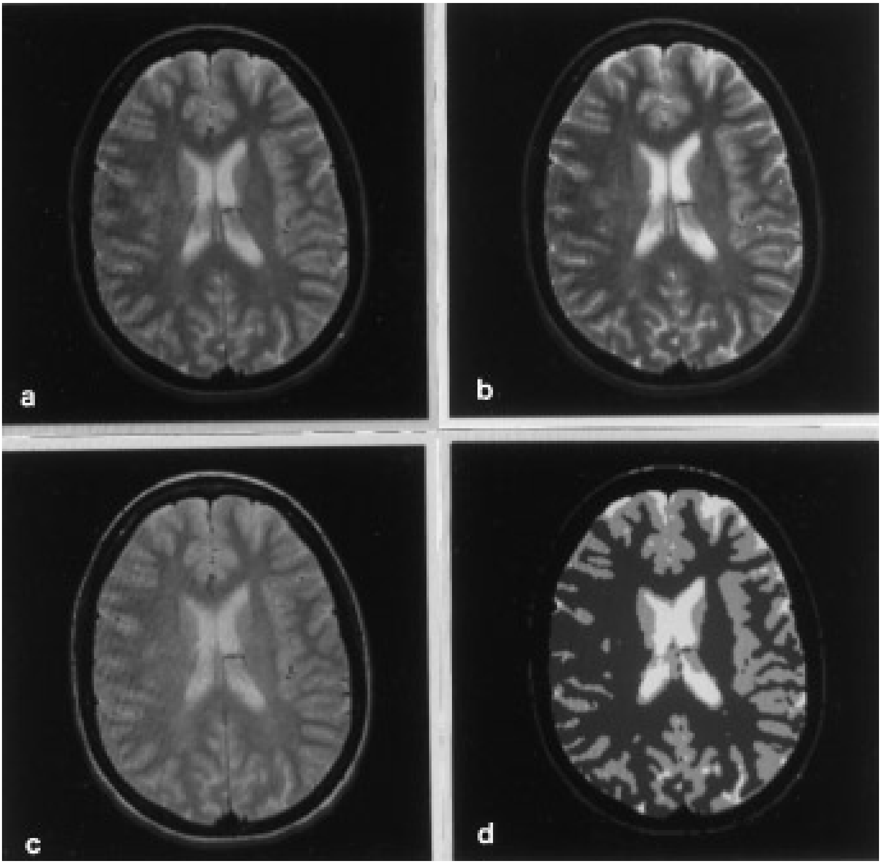

FIG. 2. The multispectral T_2-weighted brain MR images and segmented image: (a) TR/TE = 2500 ms/75 ms; (b) TR/TE = 2500 ms/100 ms; (c) TR/TE = 1500 ms/55 ms; (d) segmented result with 4 clusters.

It is difficult to compare different image segmentation methods (*30*) and to assess the accuracy of the segmented results. Nevertheless, the major criterion for performance evaluation is whether the method can indicate interesting or important regions in the image. A segmentation method can, therefore, be declared successful if it can identify the desired and most important components. For instance, Fig. 1, the segmented result can outline the CSF, the white matter, and the gray matter from the transaxial MR images of the brain. The results produced by the proposed penalized fuzzy competitive learning network are found to be in acceptable visual agreement with human expert opinion.

CONCLUSIONS

The penalized fuzzy clustering-based competitive learning network for segmentation of multispectral MR images was investigated to compute automatically, and with no operator invervention in this study. This approach requires setting

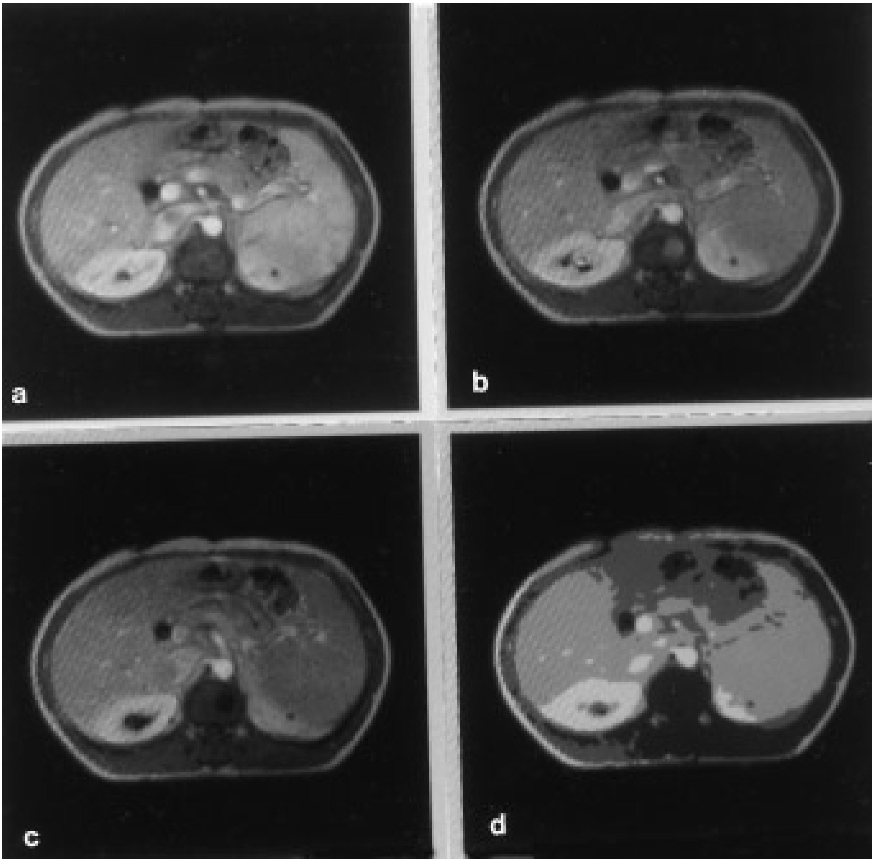

FIG. 3. The multispectral T_2-weighted peritoneal cavity MR images and segmented image: (a) $TR/TE = 2500$ ms/130 ms; (b) $TR/TE = 2500$ ms/144 ms; (c) $TR/TE = 2500$ ms/158 ms; (d) segmented image with 5 clusters.

a number of different compartments in the test images, as well as a fuzzification parameter (m) that determines the amount of overlap of cluster boundaries. It can be found that within a fairly wide range of value of m, the overall results are stable, and that the final results are independent of the initial cluster centroids in experiments. Though the fuzzy reasoning would take more computation time, the penalized fuzzy competitive learning network could provide a more efficient mechanism and powerful performance to medical image segmentation in parallel processing using the hardware implementation.

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