A fuzzy-soft competitive learning algorithm for ophthalmological MRI segmentation

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Abstract: In this paper, we consider a fuzzy-soft competitive learning algorithm (FS-CLA) which is a sequential type of the fuzzy-soft learning vector quantization (FS-LVQ). The FS-CLA is a competitive learning with a fuzzy relaxation technique by using fuzzy membership functions as kernel type neighborhood interaction functions. We then apply the FS-CLA to magnetic resonance image (MRI) segmentation for a real case of ophthalmology recommended by a Neurologist with MR image data. The algorithm is used in segmenting the ophthalmological MRI data for reducing medical image noise effects with a learning mechanism. These segmentation results demonstrate that the proposed FS-CLA is useful for use in MRI segmentation as an aid for support diagnoses.

Key–Words: Competitive learning network; fuzzy c-means; fuzzy-soft competitive learning algorithm; image segmentation; magnetic resonance image.

1 Introduction

Artificial neural networks have been studied for many years and widely applied in various areas such as image processing, signal processing, pattern recognition and vector quantization [3],[4],[7],[9]. In neural net models, the competitive learning network is an approach to unsupervised learning and is used most in vector quantizer design and clustering. The k-means (or called hard c-means) clustering is a batch algorithm for designing a vector quantizer, which is a mapping of input vectors to one of c predetermined codevectors (also called codebooks) [10]. Fuzzy c-means (FCM) clustering is a fuzzy extension of hard c-means clustering. The FCM and its varieties have been widely studied and applied in various areas [1],[5],[13],[14]. The fuzzy membership functions from FCM algorithms give good cluster membership interpretations. Incorporating these fuzzy membership functions into neural networks becomes a reasonable way to make fuzzy types of neural computing. Keller and Hunt [6] first incorporated fuzzy membership functions into the perceptron algorithm and created a so-called fuzzy perceptron. For a batch-type learning vector quantization (LVQ), Wu and Yang [12] proposed a fuzzy-soft LVQ (FS-LVQ) based on fuzzy membership functions.

In this paper, we create the fuzzy-soft competitive learning algorithm (FS-CLA) which is modified from FS-LVQ and becomes a sequential type of FS-LVQ. The proposed FS-CLA is with a competitive learning by incorporating a fuzzy relaxation technique using fuzzy membership functions as a kernel type of neighborhood interaction function. We then apply the FS-CLA to the magnetic resonance imaging (MRI) segmentation. A real case recommended by a Neurologist is examined. The patient suffered bilateral internuclear ophthalmoplegia, which indicates lesions in the bilateral medial longitudinal fasciculus in the tegmentum of the dorsal pons. The brain MRI revealed lacunar infarctions in the bilateral lentiform nuclei, thalami and corona radiate, but not in the pons. For the purpose of enhancing the lesions from the MRI noise, the FS-CLA is used to reduce medical image noise effects with learning mechanisms. The results from segmenting the MRIs of ophthalmology show that the FS-CLA gives good results.

2 A fuzzy-soft competitive learning algorithm

Neural network models can roughly be divided into three categories: feedforward networks (e.g. mutilayer perceptron), feedback network (e.g. Hopfield network) and competitive learning network (e.g. SOM) [7],[8],[9]. Both feedforward and feedback networks are supervised. The competitive learning network is unsupervised. Competitive learning is moti-

vated by the anatomical and physiological evidence of lateral interaction between neurons in mammalian nervous systems. The lateral neural interaction of competitive learning can be approximated using the well-known winner-take-all (WTA) principle. Only the winner in neural learning is allowed while other neurons are inhibited. Suppose that the s-dimensional feature vector x_j, $j = 1, \cdots, n$, is the input data at time t, the Euclidean winner among the c neurons $(Z_i, i = 1, \cdots, c)$ is then produced upon the nearest neighbor condition. That is, neuron i is the winner at time t when x_j is input if

$$\|x_j - Z_i(t-1)\| = \min_{1 \le k \le c} \|x_j - Z_k(t-1)\|. \quad (1)$$

The learning can then be described according to the learning formula

$$\begin{cases} \text{If } Z_i(t-1) \text{ is the winner,} \\ \quad Z_i(t) = Z_i(t-1) + \alpha(t)(x_j - Z_i(t-1)); \\ \text{If } k \neq i, \\ \quad Z_k(t) = Z_k(t-1) \end{cases} \quad (2)$$

where $\alpha(t)$ is called the learning rate and is confined to decrease monotonically with time t. The winner after competitive learning will be updated towards the input vector with a step size $\alpha(t)$. Other neurons are unchanged. The learning will stop when the network is stable. Thus, the WTA learning algorithm based on equations (1) and (2) can be summarized as follows:

WTA algorithm

Initialize $Z_1(0), \cdots, Z_c(0)$ and α;
For t=1,$\cdots$,T; $\alpha(t) = \alpha/t$;
  For j=1,$\cdots$,n;
    Update $Z_i(t)$ using (1) and (2);
  Next j;
Next t.

We know that the k-means (or hard c-means) clustering can be thought of as a batch version of the WTA algorithm. The fuzzy c-means (FCM) clustering is a fuzzy extension of hard c-means clustering. The FCM and its varieties have been widely studied and applied in various areas. The fuzzy membership functions from FCM give a good interpretation of cluster memberships for most real cases. Let X be a subset of an s-dimensional Euclidean space $\mathbf{R^s}$. A fuzzy $c-$partition $\{\mu_1, \cdots, \mu_c\}$ of X into c clusters consists of the fuzzy sets μ_i assuming values in the interval $[0, 1]$ such that $\sum_{i=1}^{c} \mu_i(x) = 1$ for all x in X. The FCM is a clustering algorithm to find optimal fuzzy $c-$partitions and optimal $c-$means for a data set $X = \{x_1, \cdots, x_n\}$. Tsao et al. [11] and Bezdek and Pal [2] constructed the so-called fuzzy Kohonen clustering networks (FKCN) and fuzzy learning vector quantization (FLVQ). FKCN and FLVQ were proposed to integrate the FCM clustering with the Kohonen network. FKCN and FLVQ can be seen as a (batch) Kohonen type of learning FCM clustering using a decreasing fuzzifier (fuzziness) m_t of the FCM objective function to 1 (i.e. $m_t \to 1$ as $t = 1, 2, \cdots, t_{\max}$) so that they can converge faster than the FCM clustering. In Wu and Yang [12], a batch-type LVQ, called a fuzzy soft LVQ (FS-LVQ), based on fuzzy membership functions which has a different learning mechanism from FKCN and FLVQ was proposed. Wu and Yang [12] also provided numerical comparisons of FSLVQ to FLVQ and FCM.

Next, we create the fuzzy-soft competitive learning algorithm (FS-CLA). The FS-CLA is modified from the FS-LVQ. The FS-CLA can be seen as a sequential type of FS-LVQ. The neural lateral interaction and learning rates are approximated using fuzzy membership functions and all neurons are updated according to the following learning formula:

$$Z_k(t) = Z_k(t-1) + \alpha_i(t) h_{i,k}(t)(x_j - Z_k(t-1)), i = 1,..,c, j = 1,..,n \quad (3)$$

where $h_{i,k}(t)$ denotes the degree of excitation of the neurons. The FS-CLA is constructed as a parameter-free scheme. We define $\mu_i(x_j)$ as the fuzzy membership of x_j that $Z_i(t-1)$ wins with the well-known FCM membership functions (see Refs. [1],[5],[13])

$$\mu_i(x_j) = \frac{\|x_j - Z_i(t-1)\|^{-2/(m-1)}}{\sum_{k=1}^{c} \|x_j - Z_k(t-1)\|^{-2/(m-1)}} \quad (4)$$

and $m = 2$ is typically used. We then approximate the neural lateral interaction using

$$h_{ij}(t) = \left[\frac{\mu_i(x_j)}{\max_{1 \le i \le c} \{\mu_i(x_j)\}} \right]^{(1 + \frac{f(t)}{c})}, \; i = 1, \cdots, c, \quad (5)$$

where $f(t)$ is a positive strict monotone increasing function of t that controls the degree of excitation. Typically, $f(t) = t$ or $f(t) = \sqrt{t}$. We used the function $f(t) = \sqrt{t}$ in this paper.

In the fuzzy-soft competitive learning, $f(t)$ is confined as strictly increasing with

$$\lim_{t \to \infty} f(t) = \infty \quad (6)$$

and the competitive learning is soft with

$$0 \le h_{ij}(t) \le 1. \quad (7)$$

It is easy to show that when t tends to infinity, the learning rule in the fuzzy-soft network will tend toward WTA. That is $\lim_{t\to\infty} h_{ij}(t) = 1$ if $Z_i(t-1)$ satisfies the nearest neighbor condition (1) and 0 otherwise. When t tends to infinity, only the neuron that is the closest to the input data will be excited and other neurons will be inhibited. The function $f(t)$ can determine the decreasing rate from fuzzy-soft competitive learning to hard competitive learning (i.e. WTA). The neuron number c is also an important factor as we control the decreasing rate. The rate should be relatively slow as c is large and relatively fast as c is small. Therefore, we use $f(t)/c$ as an overall consideration. We may also choose any other positive strictly increasing functions for $f(t)$ to control the excitation states.

Using the normalization term $\max_{1\le i\le c}\{\mu_i(x_j)\}$ in equation (13) is important. The membership functions $\mu_i(x_j)$ resulting from FCM have the restriction with $\sum_{i=1}^{c} \mu_i(x_j) = 1$. Suppose the network is trained with a large codebook and bad initial weights, the $\mu_i(x_j)$ for each i will then be very close to a small positive number $1/c$ when c is large. Our normalization technique can ensure that the excited state of the closest neuron is one and the learning will have relative significance at each step.

In WTA, the learning rates $\alpha_i(t)$ for neurons at time t are all equal with $\alpha_i(t) = \alpha(t) = \alpha/t$. In the fuzzy-soft competitive network, the decreasing gaps $\alpha_{ij}(t)$ will be controlled by the excited states as

$$\alpha_{ij}(t) = \frac{\alpha_0}{[\,\frac{\alpha_0}{\alpha_{ij}(t-1)}\,] + h_{ij}(t)}. \qquad (8)$$

In each time t, neurons with small excited states will have small decreasing gaps and will then maintain their competitive learning potential. The decreasing gaps are dependent on their individual excited levels. This update schedule efficiently builds a fair competitive learning environment and can be also written as

$$\alpha_{ij}(t) = \frac{\alpha_0}{[\,\frac{\alpha_0}{\alpha_i(0)}\,] + \sum_{l=1}^{t}\sum_{k=1}^{j} h_{ik}(l)}. \qquad (9)$$

Since α_0 and $\alpha_i(0)$ are positive constants, the learning rate (9) in the fuzzy-soft network shall decrease monotonically to zero as the time t increases. The decreasing gap is controlled by adding the new excited state $h_{ij}(t)$ to the previous total excited values to the denominator. Note that α_0 can be used to control the decreasing rate of learning. A large value for α_0 means a small decrease in the learning rate. Thus, the FS-CLA can ensure that the learning size of the neuron with a large excited state will be relatively large under the same starting learning conditions. We create the FS-CLA algorithm as follows :

FS-CLA algorithm

Initialize $Z_1(0), \cdots, Z_c(0)$;
For t=1,$\cdots$,T;
  For j=1,$\cdots$,n;
    Estimate $h_{ij}(t)$ using (4) and (5);
    Update $\alpha_{ij}(t)$ using (8);
    Update $Z_i(t)$ using (3);
  Next j;
Next t.

3 MRI segmentation

A real Ophthalmology case recommended by a Neurologist with MR image data is examined in this section. A male patient, age 79, was admitted to the hospital for a sudden onset of double vision that lasted for ten days. Over the past several years, he suffered from hypertension, ischemic heart failure and chronic atrial fibrillation. He then received cardioversion. A neurological examination upon admission revealed only bilateral internuclear ophthalmoplegia, indicating lesions in the bilateral medial longitudinal fasciculus in the dorsal pons tegmentum. There was no weakness in his extremities. A standard spin-echo (SE) sequence with TR=2650 ms with TE=82.9 produced MR Images with a field of view (FOV)=24*18 mm, Slice thickness= 5.0 mm without gap and a 256*256 pixel matrix, that is, contiguous slices were acquitted. This patient's brain MRI revealed lacunar infarctions in the bilateral lentiform nuclei, thalami and corona radiate, but not in the dorsal pons. The diffusion-weighted images did not show recent or acute infarctions. Because the clinical findings were consistent with dorsal pontine lesions, he was discharged two days later under a bilateral internuclear-ophthalmoplegia diagnosis probably due to the bilateral dorsal pontine infarct. His double vision disappeared in about a month. Thus, the proposed FS-CLA is used in segmenting the patient's MRI data with comparisons of the WTA. The segmentation results are introduced as a support for clinical diagnosis.

The above actual MRI data set was implemented on the FS-CLA and WTA learning algorithms. For the patient, age 79, suffered with a sudden onset of double vision for 10 days, neurological examination revealed only bilateral internuclear opthalmoplegia, indicating lesions in the dosal pons. However, the MR image shown in Fig. 1 did not reveal the lacunar infarctions in the pons area. MRI may be helpful in the clinical

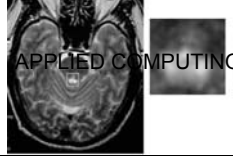

Fig. 1 Original MR Image with selected window

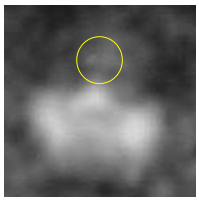

Fig. 1.1 Original selected window MR Image

Table I
Accuracy with R, G, B, and computational efficiency NI for the MRI data set from the patient with bilateral internuclear ophthalmoplegia

Initial	WTA		FSCLA	
	NI	Accurac	NI	Accurac
20,80,130,160,180	48	G	20	R
20,80,140,160,180	48	G	20	R
20,80,150,160,180	48	G	19	R
20,80,160,180,200	49	G	19	G
20,80,160,220,240	49	B	21	B

R: Refined accuracy G: Good accuracy B: Bad accurac
Image size = 168*168(28224) pixels, Max T = 50, class = 5, $\varepsilon = 0.01$

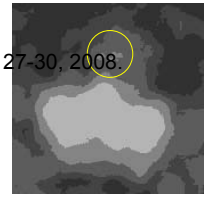

Fig. 2
Refine Accuracy from FS-CLA

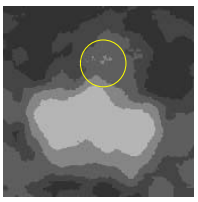

Fig. 2.1
Good Accuracy from FS-CLA

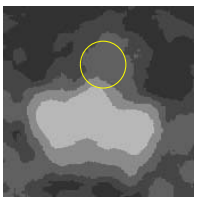

Fig. 2.2
Bad Accuracy from FS-CLA

diagnosis of brain leasons. However, it has limitations in detecting lesions and tumors as small as $0.01mm^3$ and digital noise from sensor resolution. The competition learning segmentation techniques are useful in detecting small lesions. They are more helpful in outlying the edge between tissues from digital image noise. To enhance the lesions, under the recommendation of specialists, grayscale window segmentation around the dosal pons area is selected (see Fig. 1.1) from the original MR image. The window image is grouped into five tissue classes: edema, gray matter, nerve tissue, white matter and cerebrospinal fluid. The gray scale histogram chooses from the 168*168 pixels window segmentation, providing a set of starting points. We analyzed the accuracy and the computational efficiency of the lesions detected from the window MRI data set against the WTA and FS-CLA algorithms.

The computational efficiency is calculated by the number of iterations (NI). All algorithms were processed with the same specifying initial vectors Z(0), stopping criterion ϵ =0.01 and maximum NI=50. The histogram gray scale ranges from 0 to 255 starting from dark to bright. In this MRI data set, the histogram suggested that the lesion peak is around 140, which is in the middle of five initials Z(0) . Therefore, we simulated the test by changing the third initials from 130 to 160 to examine the accuracy and computation efficiency. Furthermore, we tried to compare the learning ability for WTA and FS-CLA by pulling the initial vector away from the lesion peak. According to the histogram, a good starting initial vector set is $\{20, 80,140,160,180\}$. We then set the initial vector set as $\{20, 80,160,220,240\}$, which pulls the 4th and 5th initial vectors toward the bright side of the gray scale to test the performance of these competitive learning algorithms. The pictures from Fig. 1.1 were processed at 168*168 pixels and clustered into five tissue classes. From the red circle on the two dimensional MR images, two node shaped detailed lesions displayed at the dosal pons of the brain was pointed out by the neurologist and radiologist.

The MR image data set shown in Fig. 1.1 was simulated using FS-CLA and WTA. The segmentation results are shown in Fig. 2 and Fig. 3, respectively. We compared these two competitive learning algorithms by moving the third initial vector toward both sides of the grayscale. Furthermore, we tried to compare the learning ability of all three algorithms by simulating a set of initial vectors that were based on the histogram peaks. The results are listed in Table I. The data varies in NI and accuracy when the gap between the 3rd initial vector and 4th initial vector are closer. However, unequal quantities of MRI data set grayscale pixels to these three algorithms may affect the performance and the accuracy of R, G and B where R denotes the refined accuracy; G denotes good accuracy and B denotes bad accuracy. Therefore, the set of starting initial vectors suggested from the histogram peak is more essential.

With a set of good initial vectors referenced from the MR image data set histogram, FS-CLA produced the most refined and accurate image (see Table I and Fig. 2). In the red circle, it shows two detailed lesion nodes at the pons area. According to our experimental results, FS-CLA provides refined accurate segmentation images that enhance the two lesions at the pons area of the brain. The iteration number to converge is also faster than the WTA. Overall, the physicians recommended using FS-CLA as an aid to brain lesion

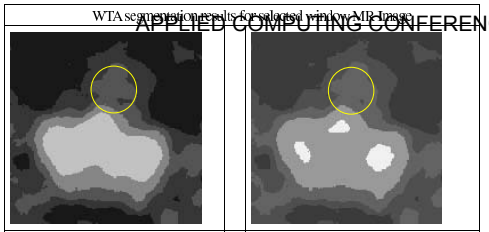

Fig. 3
Good Accuracy from WTA

Fig. 3.1
Bad Accuracy from WTA

medical diagnosis.

4 Conclusions

In this paper, a sequential type FS-CLA is created. Since the concept of fuzzy-soft competitive learning is used in FS-CLA where the fuzzy-soft learning can build a more fair and reasonable competitive neural environment, it provides a more stable competitive learning network. We also found that the FS-CLA is a parameter-free scheme. We apply the FS-CLA in segmenting an actual ophthalmological MRI data set. MRI has limitations due to the size of the lesion area. This may be caused by digital noise in the partial volume effects originality from the low sensor resolution. As a result, in using the FS-CLA algorithm , the large learning size with a large excited state will remain as a relatively large learning condition. Thus, the learning pixel quantities of the lesions may affect the NI and accuracy of the lesion outline. As it is more robust, the FS-CLA has the ability to tolerate the above situations both in the number of iterations and the accuracy of the lesion outline. Therefore, we recommend the FS-CLA for use in MRI segmentation as an aid for support diagnoses.

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