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Suppressed fuzzy-soft learning vector quantization for MRI segmentation

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ABSTRACT

Objective: A self-organizing map (SOM) is a competitive artificial neural network with unsupervised learning. To increase the SOM learning effect, a fuzzy-soft learning vector quantization (FSLVQ) algorithm has been proposed in the literature, using fuzzy functions to approximate lateral neural interaction of the SOM. However, the computational performance of FSLVQ is still not good enough, especially for large data sets. In this paper, we propose a suppressed FSLVQ (S-FSLVQ) using suppression with a parameter learning schema. We then apply the S-FSLVQ to MRI segmentation and compare it with several existing methods.

Methods and materials: The proposed S-FSLVQ algorithm and some existing methods, such as FSLVQ, generalized LVQ, revised generalized LVQ and alternative LVQ, are compared using numerical data and MRI images. The numerical data are generated by a mixture of normal distributions. The MRI data sets are from a 2-year-old female patient who was diagnosed with retinoblastoma of her left eye, a congenital malignant neoplasm of the retina with frequent metastasis beyond the lacrimal cribrosa. To evaluate the performance of these algorithms, two criteria for accuracy and computational efficiency are used.

Results: Comparing S-FSLVQ with FSLVQ, generalized LVQ, revised generalized LVQ and alternative LVQ, the numerical results indicate that the S-FSLVQ algorithm is better than the other algorithms in accuracy and computational efficiency. Moreover, the proposed S-FSLVQ can reduce the computation time and increase accuracy compared to existing methods in segmenting these ophthalmological MRIs.

Conclusions: The proposed S-FSLVQ is a good competitive learning algorithm that is very suitable for segmenting the ophthalmological MRI data sets. Therefore, the S-FSLVQ algorithm is highly recommended for use in MRI segmentation as an aid for supportive diagnoses.

1. Introduction

Artificial neural networks are a data processing system consisting of a large number of simple, highly interconnected processing elements in an architecture inspired by the structure of the cerebral cortex in the human brain. This system performs two major functions: learning and recall. Learning is the process of adapting connection weights in an artificial neural network to produce the desired output vector in response to a stimulus vector presented to the input buffer. Recall is the process of accepting an input stimulus and producing an output response in accordance with the network weight structure. The learning rules of neural computation indicate how connection weights are adjusted in response to a learning example. In supervised learning, an artificial neural network is trained to give the desired response to a specific input stimulus. In unsupervised no specific response is sought, but the response based on the networks has ability to organize itself. Competitive learning, on the other hand, occurs when artificial neurons compete among themselves, and only the one that yields the best response to a given input modifies its weight to become more like the input.

Lippmann [1] presented a good tutorial review on neural computing with six important neural net models that can be used for pattern classification. Of these neural net models, the Kohonen's self-organizing map (SOM) is one of the most important ones since it is unsupervised with a competitive learning neural network that uses the neighborhood interaction set to approximate lateral neural interaction and discover topological structures hidden in the data [2,3]. Learning vector quantization (LVQ) is the simplest case of SOM and its learning rule is the well-known winner-take-all (WTA) principle, which gives crisp excitation states for each neuron. When the data sets under consideration become large, the computation time of the algorithm is more important. To see the convergence rate and speed up the learning, Kohonen [2] proposed a batch version SOM. Cheng [4] studied the convergence and ordering properties of the batch SOM. This motivates us to propose another LVQ

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algorithm. Adopting the ideas of Fan et al. [5] and Hung et al. [6], we modified Wu and Yang's [7] fuzzy-soft LVQ (FSLVQ) algorithm to propose a suppressed FSLVQ (S-FSLVQ). To select the parameter in S-FSLVQ algorithm, we propose a learning process which is based on an exponential separation strength between weights with updating at each iteration. Numerical examples are used to illustrate the effectiveness of the proposed S-FSLVQ algorithm.

In oncology, physicians depend on different clinical frameworks, different types of anatomical evidence and different theoretical approaches to diagnose patients. Magnetic resonance image (MRI) approaches are particularly helpful in clinical oncology to support the diagnosis of retinoblastoma, a congenital oncological disease in ophthalmology, which usually shows its symptoms in early childhood. In this paper, the proposed S-FSLVQ algorithm is applied for the segmentation of the MRI of a retinoblastoma patient who was diagnosed using MRI in the ophthalmology field.

The rest of this paper is organized as follows. Section 2 is a brief survey of related work on LVQ algorithms. In Section 3, we introduce the batch FSLVQ algorithm. In Section 4, the S-FSLVQ algorithm with a parameter learning schema is proposed and experimental results in comparison with a variety of data sets are presented. In Section 5, we apply the S-FSLVQ to an MRI segmentation in the case study of a patient diagnosed with retinoblastoma of her left eye. In comparison with some existing LVQ algorithms for these MRI segmentation results, we find that the proposed algorithm provides better detection of abnormal tissue than others, especially in reducing the CPU time. Finally, discussions and conclusions are presented in Sections 6 and 7, respectively.

2. Related work

Kohonen's SOM is an unsupervised competitive neural network that uses the neighborhood interaction set to approximate lateral neural interaction and discovers the topological structure hidden in the data for visual display in one or two dimensional space [3]. Although Kohonen's competitive learning network originally was not a clustering method, it could be used as a prototype generation algorithm called a LVQ [3]. Because LVQ updates only the winner node, Pal et al. [8] proposed a generalization of LVQ (GLVQ) that updates all nodes for given input data with the learning rule depending on the degree of distance match to the winner node. Based on the winner-take-most competing strategy, Karayiannis and Pai [9], Karayiannis [10] and Karayiannis et al. [11] proposed some fuzzy generalized LVQ (FGLVQ) algorithms. Zhou et al. [12] discussed the disadvantages of GLVQ and FGLVQ algorithms and then proposed a revised generalized LVQ (RGLVQ) algorithm to overcome these disadvantages.

Yair et al. [13] applied the stochastic relaxation concept to modify the learning rate and neighborhood function in SOM and proposed a soft competitive learning network. Combining the competitive learning with soft competition and fuzzy *c*-means membership functions, Wu and Yang [7] proposed a batch competitive learning method called fuzzy-soft LVQ (FSLVQ). Recently, Wu and Yang [14] discussed the influences of noise and outliers on the SOM quality. To reduce the influence of noise and outliers on SOM, they proposed an alternative LVQ (ALVQ) algorithm, and numerical results have shown ALVQ performs well.

Image segmentation is a way to partition image pixels into different cluster regions with similar intensity image values. Cluster analysis is a method of clustering a data set into groups displaying similar characteristics. It is an approach to unsupervised learning and has become one of the major techniques used in pattern recognition. Therefore, clustering algorithms would naturally be applied in image segmentation. Because most MRIs present overlapping gray-scale intensities for different tissues, fuzzy clustering algorithms are widely used for MRI segmentation, such as brain MRI [15–19] and ophthalmological MRI segmentations [20]. However, these fuzzy clustering algorithms always suffer from sensitivity to initials, parameters and noise. Thus, various neural network approaches have been proposed for the MRI segmentation to overcome these problems. In these neural network approaches, Kohonen's SOM is most used in MRI segmentation. Lin et al. [21] generalized Kohonen's SOM with fuzzy and fuzzy-soft types called fuzzy Kohonen's competitive learning and fuzzy-soft Kohonen's competitive learning. They applied these generalized Kohonen's competitive learning algorithms to MRI and magnetic resonance angiographies (MRA) ophthalmological segmentations. Recently, Yang et al. [22] applied the FSLVQ algorithm to three MRI data sets of real cases: (i) a 2-year-old girl who was diagnosed with retinoblastoma in her left eye; (ii) a 55-year-old woman who developed complete left side oculomotor palsy immediately after a motor vehicle accident; and (iii) an 84-year-old man who was diagnosed with Alzheimer's disease. Yang et al. [22] also compared the performance of FSLVQ algorithm with the generalized Kohonen's SOM algorithms proposed by Lin et al. [21]. The results indicated that the FSLVQ algorithm is better than these generalized Kohonen's SOM algorithms.

3. Batch fuzzy-soft LVQ

The SOM [2,3] is a useful tool for visualizing high-dimensional data. Basically, it produces a similarity graph of input data and converts the nonlinear statistical relationships between high-dimensional data into simple geometric relationships of their image points on a low-dimensional display, usually a regular two-dimensional grid of nodes. That is, SOM is a two-layer feed-forward competitive learning neural network that can discover a topological structure hidden in the data and display it in one or two-dimensional space. Assume that W_k in an p-dimensional Euclidean space R^p with its ordinary Euclidean norm $||\cdot||$ is the specified weight of the node k and the feature vector $x_j \in R^p$ is shown on-line at time t, the winner neuron k among all neurons is produced by the nearest neighbor condition

$$||x_j - W_k(t-1)|| = \min_i ||x_j - W_i(t-1)||. \tag{1}$$

Eq. (1) indicates that the weight of node k matches best with x_j. Then the self-organization used the following learning rule:

$$W_i(t) = W_i(t-1) + \alpha_i(t) h_{i,j,k}(x_j - W_i(t-1)), \tag{2}$$

where $\alpha_i(t)$ is the learning rate of the node i and is a monotonically decreasing function of time t. The neighborhood function $h_{i,j,k}$ is the lateral neural interaction phenomenon and the degree of excitation of the neuron. Usually, $h_{i,j,k}$ is defined as

$$h_{i,j,k} = \begin{cases} 1, & \text{if the node } i \text{ belongs to } N_k(t), \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

$N_k(t)$ is called the neighborhood set of the winner neuron k and is a decreasing function of time t because it needs to match the WTA principle. It means that when $t \to \infty$,

$$h_{i,j,k} = \begin{cases} 1, & \text{if } i = k, \\ 0, & \text{if } i \neq k. \end{cases} \tag{4}$$

It is well-known that LVQ for unlabelled data can be viewed as a special case of SOM. In LVQ, the neighborhood set of each node will contain the winner node and hence the vectorial location of the node is negligible. This competitive learning rule is called the WTA and the neighborhood function is defined as Eq. (4). From Eq. (2), we know that, after an on-line feature vector x_j is input, the weights of the nodes in both SOM and LVQ will update toward the input