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Stability Study of Some Neural Networks Applied to Tissue Characterization of Brain Magnetic Resonance Images

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Abstract

This study investigates the segmentation ability of unsupervised clustering of the image feature space. A self-organizing map, a feed-forward neural network, and a k-nearest neighbor classifier were compared in labeling brain slices from magnetic resonance imaging. Qualitative and quantitative tests were carried out using brain images of a patient with an infarction. Five different tissue classes were partitioned: white matter, gray matter, cerebrospinal fluid, fluid in the infarct region, and gray matter in the infarct region. The SOM based method performed best in all the cases that were investigated. Especially, the stability of the method concerning the influence of the training set was superior.

1. Introduction

Imaging examinations of patients belong to the most widely used diagnostic procedures in modern medicine. Of all the different imaging techniques, magnetic resonance imaging (MRI) has a unique advantage: it is multispectral in nature. Using different pulse sequences, multiple images from the same anatomical location can be obtained.

Routinely, the images are interpreted visually and qualitatively by human experts. However, the need for quantitative information is becoming increasingly important. The quantitative volume measurements of different brain tissues allow the tracing of anatomical alterations. A semi-automatic segmentation method would enable investigations on statistically relevant patient groups, while the huge amount of data forbid manual segmentation. Therefore, a very important condition for such a method is minimal human interaction.

Statistical segmentation methods such as the fuzzy c-mean algorithm or the k-nearest neighbor (k-nn) [8, 1] classifier have been widely used. Restricted to neural network approaches, most of the research work published so far has been done using feed-forward networks trained by fully supervised learning algorithms [2, 6].

The stability of the segmentation, in relation to the training set and the intensity variations through different slices, is of special interest. Fully supervised methods adapt strongly to the training set and suffer from intensity variations between slices. In this study the possibility of using self-organizing maps (SOM) for segmentation of brain MR images was investigated. The results were compared with those of a backpropagation (BP) trained feed-forward network and a k-nn classifier. The tests were performed using real medical data. The results were validated qualitatively by a neuroradiologist and quantitatively using a test set.

2. Methods

2.1. Images

The methods were applied to brain MR slices (figure 1) of a 73 years old male patient with an infarction about three months old. The imaging was performed in Helsinki University Central Hospital using a Siemens Magnetom SP42 (1 T) MRI scanner. Each slice size consisted of 256x256 pixels and there were continuous slices from 26 locations. Three slices were taken from each location: proton density (PD, TR=3000 ms, TE=20 ms), T2 (TR=3000 ms, TE=80 ms) and T1 (TR=400 ms, TE=15 ms) weighted. The pixel size was 0.9 x 0.9 mm^2 and the slice thickness 5 mm.

The images were segmented to five different tissue classes: white matter (WM), gray matter (GM), cerebrospinal fluid (CSF), fluid in the infarct region (ICSF), and gray matter in the infarct region (IGM). Besides the large infarction region, the classification was complicated by alterations in the tissue intensities, due to normal aging.

2.2. Choice and Evaluation of the Feature Vector

The choice of the features has a strong influence to the final segmentation accuracy. Basically, the three intensity values (PD, T2 and T1) of each pixel were the only information provided. A 13-dimensional feature vector was applied for all three segmentation methods tested (table 1). Combinations of different images as well as the neighborhood were included in the features. The neighborhood included the eight nearest neighbors with the four nearest weighted twice as much as the others. This was found to be a good compromise between compensating the effect of noise and on the other hand loosing resolution.

1	PD value
2	T2 value
3	T1 value
4	PD-T2
5	(PD+T2)/(PD-T2)
6	PD-T1
7	(PD+T1)/(PD-T1)
8	mean value of the neighborhood (PD)
9	standard deviation of the neighborhood (PD)
10	mean value of the neighborhood (T2)
11	standard deviation of the neighborhood (T2)
12	mean value of the neighborhood (T1)
13	standard deviation of the neighborhood (T1)

Table 1: Features consisting of the three intensity values, combinations of different images and inclusion of the neighborhood.

The additional use of relative intensity values (features 4 and 6) avoided additive errors which may occur as a consequence of intensity inhomogeneities. Feature 5 emphasized the CSF, which was also reported in [7]. The optimal weighting of the features is a delicate problem which cannot be easily solved. Discussions about the feature selection problem can be found in [4]. However, due to the early stage of this project and the results obtained the feature vector was applied without any normalization.

2.3. Self-Organizing Maps

The basic idea of the image segmentation process based on a SOM can be divided into two steps [9, 10]:

1. Unsupervised clustering of the whole feature space into m subclasses where m is the number of neurons and should not be too small.

2. Allocation of the m subgroups to the desired tissue classes using a training set provided by a neuroradiologist.

Step one was achieved using Kohonen's original learning algorithm [5]. A map containing 5*10 elements was trained using the feature vectors of 4000 randomly selected image points.

In the second step the training set was presented to the map obtained, recording to which tissue class samples the neurons reacted. While most of the neurons were clearly defined, there were also some which were activated by the samples of different classes or did not answer at all. The neurons which did not respond to any sample of the training set could be seen as representing tissue that was different from those in the set. They could define a new class, possibly useful in clinical applications. If the whole image slice were classified into the predefined tissue classes, these neurons were simply switched off. It was not sensible to relate somehow these neurons with a specific class, because the underlying distribution was not known.

The neurons responding to samples of several tissue classes signalized overlapping clusters. Image points represented by those neurons had to be classified individually. Out of the possible methods, the final classification was achieved using Learning Vector Quantization [5].

The main advantage of the unsupervised clustering was that every single image point had not to be compared and classified with the training set as in fully supervised methods. Only the corresponding reference vector had to be considered, giving the whole method a higher stability to small variances.

2.4. Backpropagation Feed-Forward Network

Several authors [2, 6] have reported good results using trained feed-forward networks. One important point in this approach requiring some trial-and-error experiments was the network architecture. A three layer network with 13 input, 21 hidden and 5 output nodes turned out to perform best. The neurons contained sigmoidal transfer functions. Training was stopped latest after 10 000 iterations.

2.5. K-Nearest Neighbor Classifier

The k-nn classifier is a fully supervised algorithm [8]. A 3-nearest neighborhood turned out to be most suitable in our application.

3. Tests

3.1. Single-Slice Segmentation

First one slice (#9) was selected. The neuroradiologist defined a training set and a test set with 440 and 827 samples, respectively. All the three classification methods were trained and applied. The visual inspection of the segmented images (figure 2) showed a good accuracy for all methods. However the results of the SOM based method and the k-nn classifier were better than the results of the BP network, which had some difficulties in separating correctly the CSF from the ICSF. This is also evident from table 2, showing the percentage of correctly classified samples of the test set.

	SOM	BP	k-nn
WM (%)	95.2	89.2	96.5
GM (%)	82.9	72.1	88.2
CSF (%)	89.1	63.2	94.1
ICSF (%)	90.3	72.9	88.6
IGM (%)	69.4	70.6	68.2

Table 2: The segmentation accuracy of the test set using the three methods.

A very important aspect in image segmentation is the stability with reference to the human interaction. The definition of the training set belongs to that kind of interaction. To test the stability, the slice 9 was segmented again using this time the test set as training set. Then the number of pixels with changed classification (background not included) were counted. As can be seen from table 3, the SOM based method provided the best stability.

SOM (%)	82.0
BP (%)	66.3
k-nn (%)	75.2

Table 3: The percentage of pixels classified as the same tissue using different training sets.

3.2. Interslice Segmentation

The ability to perform interslice segmentation with sufficient accuracy is one of the main tasks for clinical applications. It seems to be also the most difficult one, because the scope of intensity values of the image data can vary through the slices [3]. Inhomogeneities and artifacts alter the intensity values and lead to misclassification. To test the performance of the methods, slices 4 and 16 were segmented using the training data of slice 9. Also the SOM still represented the feature space of slice 9. As seen in figure 3 and 4, all methods distinguished accurately between infarcted and normal tissues. Problems arose with the separation of GM and WM. Especially in slice 4, the backpropagation network ignored the WM almost completely. Also the CSF was labeled mostly as ICSF. The k-nn classifier showed better performance. The CSF was recognized correctly, but the WM was classified mainly as GM. Only the SOM based method provided an accurate segmentation, as verified by the neuroradiologist. The difference in classification may be due to the ability of a classifier to adapt to the correlating features.

4. Conclusion

The present study indicated that unsupervised clustering with self-organizing feature maps leads to an accurate and stable segmentation method for MR brain images. This approach was better than the backpropagation trained feed-forward network and the k-nn classifier, especially in the case of interslice segmentation. The results were promising, since after visual inspection a human expert reported no loss of segmentation accuracy through all the slices investigated. Based on this first approach, additional research on data preprocessing and feature evaluation will enhance the segmentation performance.

5. Acknowledgment

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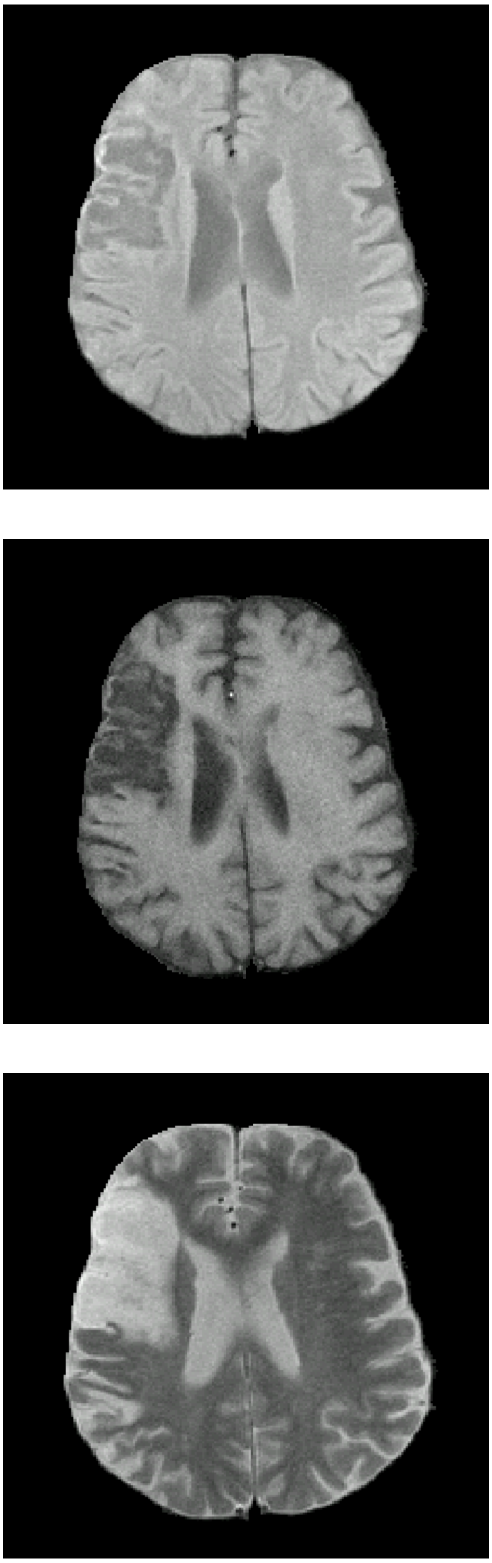

Figure 1: From top to bottom: original PD, T2 and T1 weighted images of slice 9 with removed non-brain tissue.

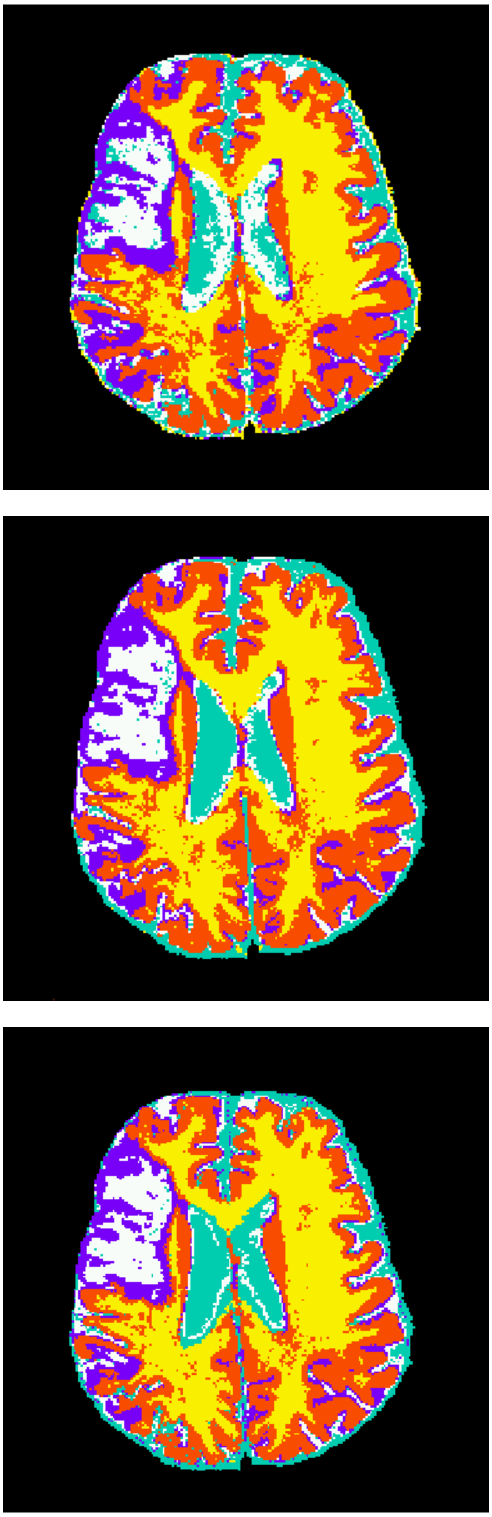

Figure 2: The segmented images of slice 9 obtained by the BP (top), the k-nn (middle) and the SOM based (bottom) methods after the removal of non-brain tissues. Yellow corresponds to WM, red to GM, green to CSF, white to ICSF and violet to IGM.

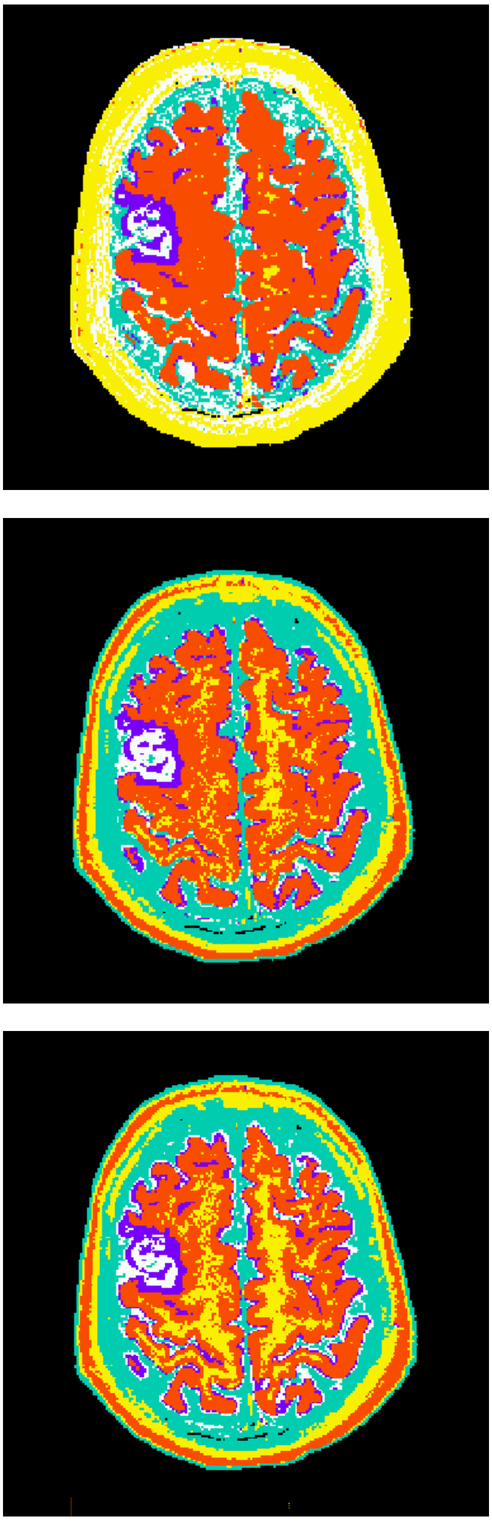

Figure 3: Interslice segmentation of slice 4. Results from BP (top), k-nn (middle), and SOM based (bottom) method. Colors are as in figure 2. The non-brain tissues are neither removed nor classified to independent classes.

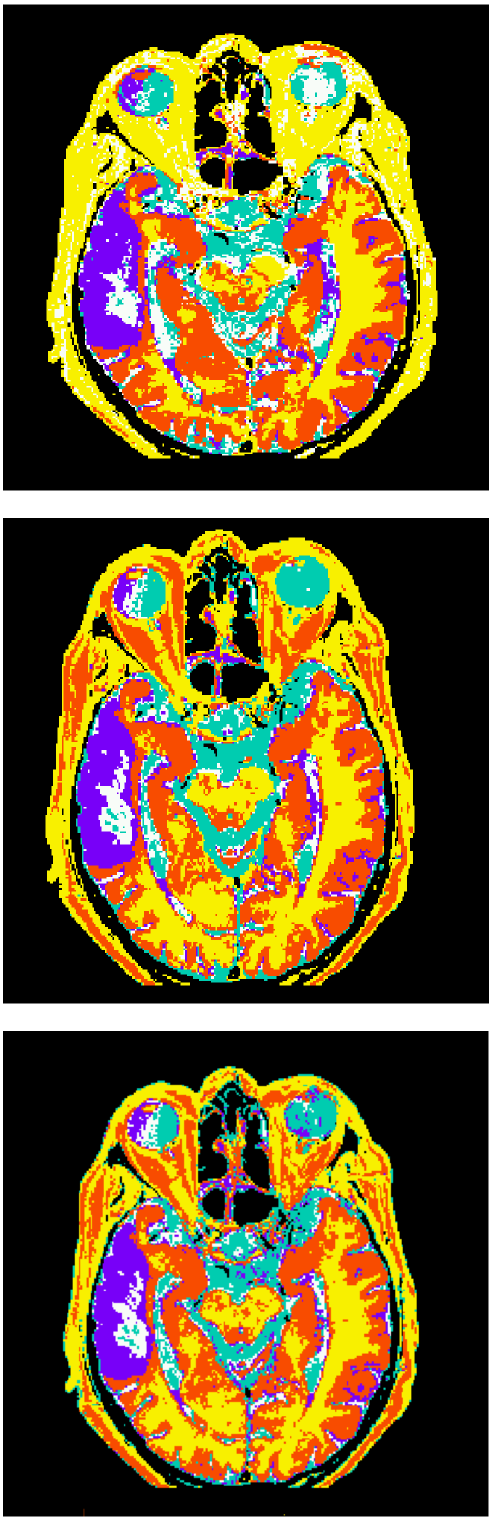

Figure 4: Interslice segmentation of slice 16. Results from BP (top), k-nn (middle), and SOM based (bottom) method. Colors are as in figure 2. The non-brain tissues are neither removed nor classified to independent classes.