IMPROVING fMRI DATA ANALYSIS BY STRUCTURED NEURAL NETWORKS

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Abstract: In fMRI data analysis artificial neural networks are a useful alternative to conventional statistical methods. Because of its advantage in analyzing time courses the Multilevel Hypermap Architecture (MHA) is used for fMRI studies with auditory stimuli. Results from investigations with the MHA show an improvement of discrimination in comparison to statistical methods. With an interface to the well known BrainVoyager software it is possible to visualize the results as a VOI.

The MHA is an extension of the Hypermap introduced by Kohonen. By means of the MHA it is possible to analyze structured or hierarchical data (data with priorities, data with context, time series, data with varying exactness), which is difficult or impossible to do with known self-organizing maps so far.

Introduction

One approach to explore stimulus related functional maps in the brain is the use of functional Magnetic Resonance Imaging (fMRI). Besides statistical methods recently artificial neural networks are used for analysis of fMRI data sets ([1, 2]). For our experiments with auditory stimuli the following structured neural network has to be introduced. The Multilevel Hypermap Architecture (MHA [3]) is classified under self-organizing neural networks and is an extension of the Hypermap introduced by Kohonen. Instead of the two levels in the Hypermap, the data and context level, the MHA supports multi-level data vectors. Structured or hierarchical data can be analyzed with the MHA, that is:

- data with priorities, e.g. representation of hierarchical data structures in databases
- data with context (databases, associative memories)
- time series, e.g. language or image scenes

Support for both the classification of data and the projection of the structure in a common map is a benefit of MHA. This results in a hierarchy with redundancy, as in biological systems. An overview of our last works about MHA gives [4].

One type of Learning Vector Quantization (LVQ) is the Hypermap principle introduced by Kohonen [5]. This principle can be applied to both LVQ and SOM algorithms. In the Hypermap the input pattern is recognized in several separate phases: the recognition of the context around the pattern to select a subset of nodes is followed by a restricted recognition in this subset. This architecture speeds up searching in very large maps and may carry out stabilizing effects, especially if different inputs have very different dynamic ranges and time constants [6]. One advantage of the MHA is the storage of hierarchical relationships of data.

The modification and extension of the Hypermap, the Multilevel Hypermap Architecture (MHA), are described in [3, 7, 8].

In addition to older experiments ([9]) a new training strategy for the MHA is introduced. The BrainVoyager software ([10]) is used for a better visualization of the results.

Materials and Methods

Even it is already published ([3, 7, 8]), it will be useful for understanding, to explain the learning algorithm of the MHA in more detail, before the fMRI environment is explained.

The system model of the MHA is shown in Fig. 1. Instead of two levels proposed in the Hypermap [5], the data and the context level, the MHA supports several levels of data relationship and therefore the input vector consists also of an arbitrary number of levels. In the MHA there is the same number of levels in the weight vector of each unit and these levels are related to the corresponding levels of the input vector. A varying number of levels for the units of the map is supported. The MHA is trained with the different levels of the input vector, whose representation is a hierarchy of encapsulated subsets of units, the so called clusters and subclusters, which define different generalized stages of classification.

The learning algorithm of the MHA as known from literature [3, 7, 8] is as follows.

Let the input vector of one level l_j be $\mathbf{x}_{l_j}$ and one processing unit $\mathbf{m}_{i,l_j}$ then, in a first phase, one has to find a first level with a subset S_j of nodes for which

$$\|\mathbf{x}_{l_j} - \mathbf{m}_{i,l_j}\| \leq \delta_j, \tag{1}$$

with δ_j being the threshold of that level. Then it is necessary to find the best match $\mathbf{m}_c$ for all nodes in the subset and to adapt the weights accordingly.

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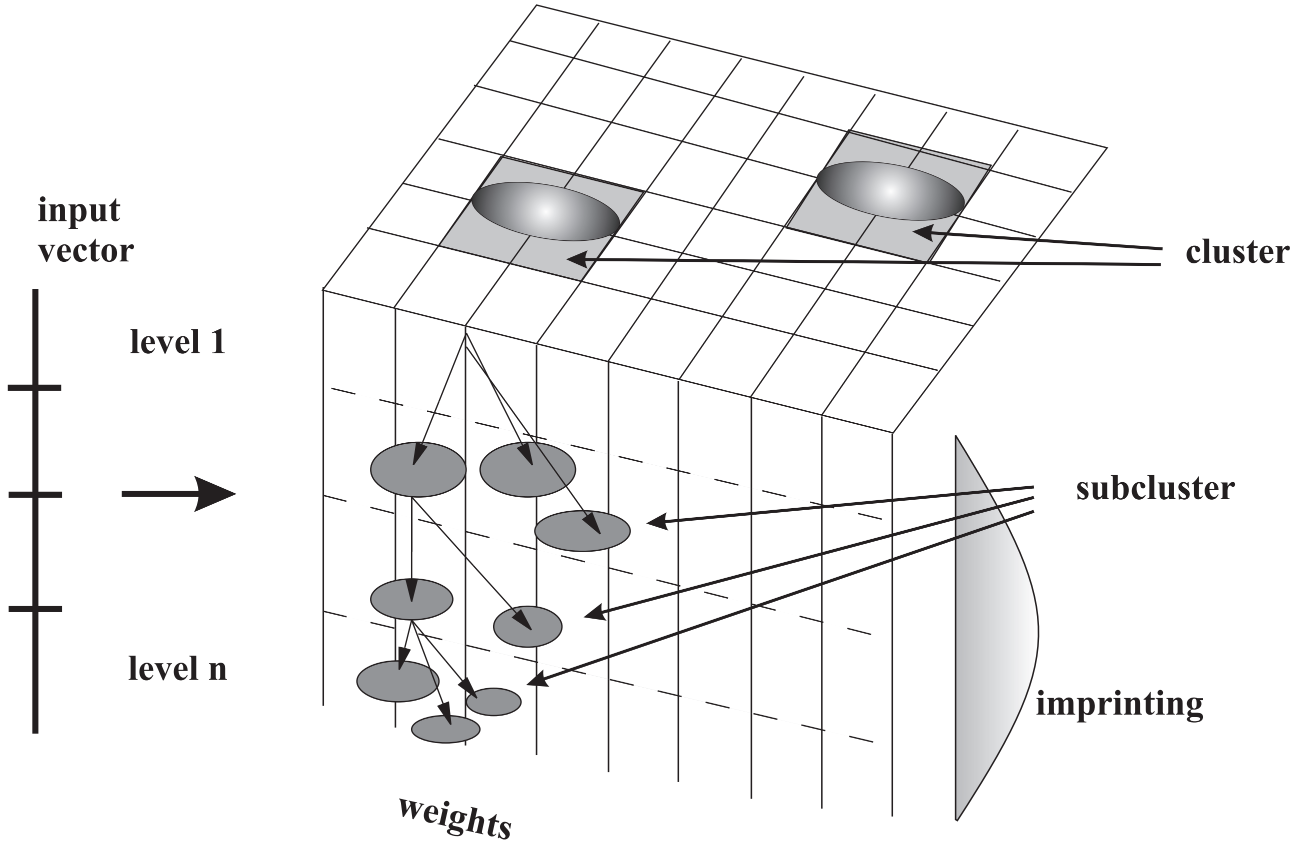

Figure 1: Multilevel Hypermap Architecture

In the normal case (input learning) the adaptation of the weights is done by

$$\mathbf{m}_{c,l_j}(t+1) = \mathbf{m}_{c,l_j}(t) + \alpha'(l_j)\alpha(t)[\mathbf{x}_{l_j}(t) - \mathbf{m}_{c,l_j}(t)], \tag{2}$$

where

$$c = arg\min_i\{\|\mathbf{x}_{l_j} - \mathbf{m}_{i,l_j}\|\}, \tag{3}$$

$$\alpha'(l_j) = e^{-\|l_i - l_j\|},\ the\ \text{"}imprinting\text{"}\ coefficient, \tag{4}$$

and

$$\alpha(t) = c_0 e^{-D(t)},\ D(t)\ distance\ function \tag{5}$$

The sizes of the thresholds δ_j should be decreased according to the order of the levels to obtain encapsulated subsets S_j. This behavior is mainly supported by the "imprinting" coefficient $\alpha'(l_j)$. Therefore the "imprinting" coefficient is responsible for the topological order of the subclusters in the MHA. Classification is achieved by finding the best matching node for each level of the hierarchy and by determining the square mean error of matching. In principle the algorithm handles different numbers of levels in the input vector.

To give more variability to the training data it is possible to mask parts of the input vector. The masked parts are ignored in the above algorithm and therefore don't influence the result of the learning process.

Important for the occurrence of the hierarchical structure of clusters and subclusters in that way is the so called imprinting coefficient (4). Without imprinting on the lower level(s) the hierarchical relationship would disappear and there will be independent data relationships on all levels of the MHA. On the other hand this feature can be useful to train a multiple set of unrelated data in one training process; each data set related to one level of the MHA. In contrast to the MHA it is impossible to detect the hierarchical order using a conventional SOM or LVQ network. The classification of data with hierarchies is of course the main advantage of the MHA learning algorithm.

In the auditory cortex of awake animals and humans responses to the same repetitive auditory stimulus will strongly habituate, dishabituate and change with general alertness, context, cognitive performances and learning. These non-stationarities are further complicated by the fact that the representation of a given stimulus in an auditory cortex field is not topographically stable over time. Several different acoustic stimuli (potpourri of various sounds, series of tones with shifting frequency, tone pairs with different frequencies) were used for the experiments with normal-hearing subjects. Subjects were scanned in a Bruker Biospec 3T/60 cm system. For principal approach and details of these experiments see also [11], [12].

Because the MHA supports several levels of data relationship and a hierarchical unsupervised clustering it is an ideal candidate for the analysis of these fMRI time series. The data was preprocessed with the well known Brain-

Voyager software [10] and VOI's were defined. Only the data of these VOI's, which represent the results of the usual statistical methods, was processed by the MHA. In a first step of our analysis of acoustic stimulated fMRI data the MHA was trained to learn the stimulus structure. With this pre-trained Hypermap the learning of the VOI-based data was continued in order to build hierarchical clusters of periodically similar data. Finally we compared our results with other methods, like statistical tests (Pearson's cross-correlation) and ICA.

Results and Discussion

As was expected and known from older experiments ([9]), the classification of the fMRI data with the MHA shows similar results in comparison to the statistical tests and ICA. But in average we get an improvement of discrimination of 15 percent. Especially by masking the stimulus relevant regions in time course the improvement can be achieved. Furthermore it is necessary to eliminate any artifacts and make a normalization (baseline, amplitude) of the data before processing by the MHA.

With the implementation of the MHA algorithm in MATLAB and the integration of an interface to BrainVoyager it is possible to visualize the classified data in VOI's. Because the stimuli were presented periodically and these periods can be built up in the multi-level structure of the MHA, the non-stationarities in these periods were detected in the hierarchy of clusters found in the MHA after training (see Fig. 2).

Conclusions

The results of our analysis of fMRI data sets by means of the MHA show, that it is possible to analyze such periodically structured and hierarchical data, what is difficult or impossible to do with other known self-organizing maps so far. Furthermore is the MHA an useful complement to conventional statistical methods in this field. Because of its character like a simultaneous auto-correlation and cross-correlation to the stimulus it has a higher selectivity and discrimination than statistical methods. In addition to standard ICA algorithms, which, by definition, are not able to estimate statistically dependent sources, the MHA has the power (e.g. by parameterization, masking of data, a-priori-knowledge) to project these dependencies in its hierarchical structure.

One advantage of the MHA is the support for both, the classification of data and the projection of the structure in one unified map. The resulting hierarchy has some redundancy like in biological systems. In the previous years some real world applications using the MHA were reported in the literature. Beside our fMRI investigations a system for speech processing and recognition [13] and an application which deals with an implementation of the Modified Hypermap Architecture for classification of image objects within moving scenes [14] are carried out.

It should be pointed out that the aim of the investigations was to test the MHA for that kind of data in principle. To find new cortical mechanisms and relevant neuronal structures with fMRI by using structured neural networks like MHA will be the next step.

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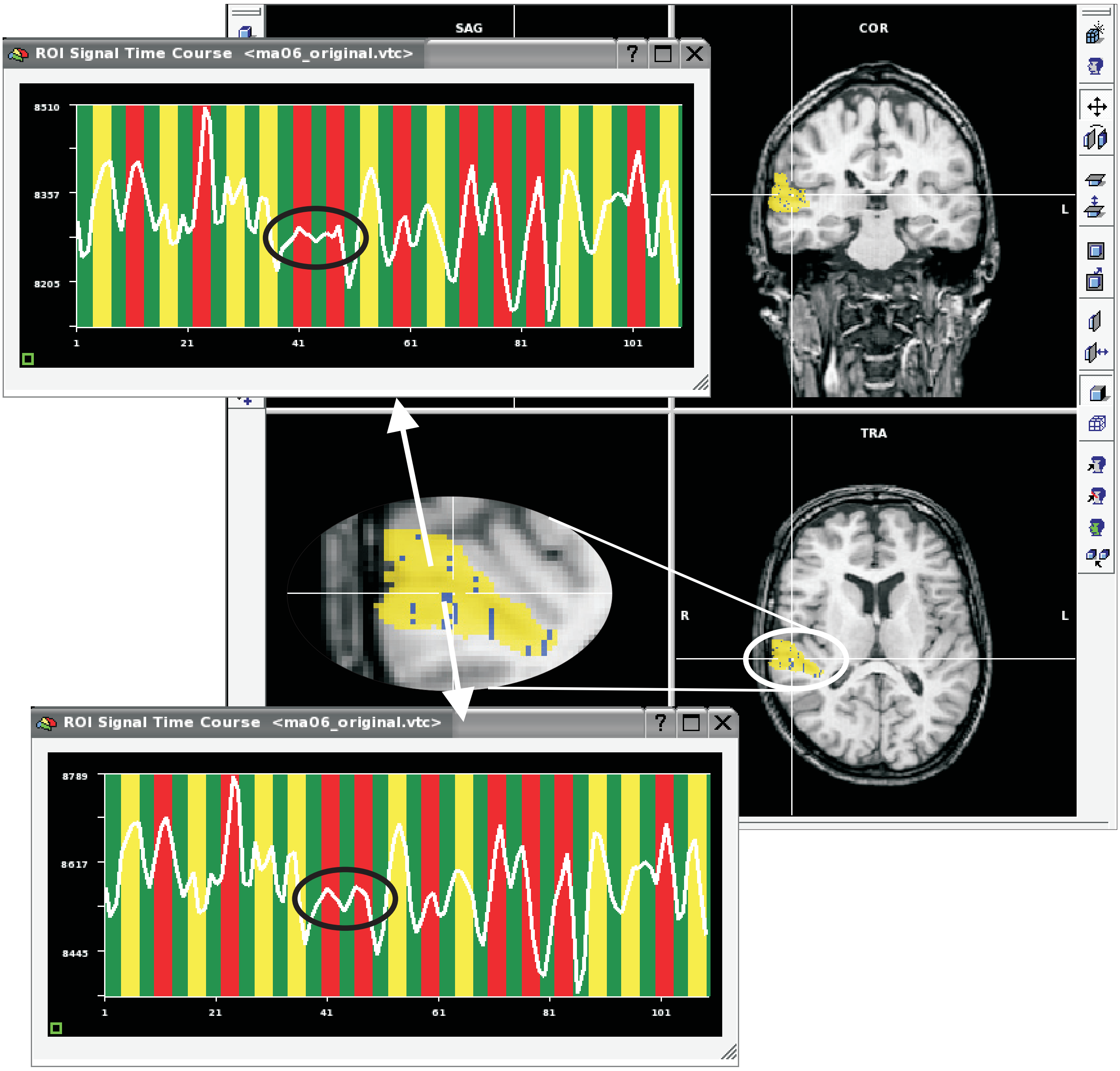

Figure 2: Results from fMRI data analysis with MHA.
VOI (in blue) represents stimulus corresponding voxels from MHA data analysis inside auditory cortex region T3 (VOI in yellow) of right hemisphere. VOI signal courses are shown for both VOI's, top (T3) and down (MHA) respectively, whereby stimulus signals are in red regions. The black circles mark one of the regions, where the improvement belonging to the stimulus discrimination is visible.

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