Fixed Point Analysis: Objective Detection of Components in ERPs and MLAEPs by a Clustering Algorithm

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Introduction

The presented work introduces a new spatiotemporal method to analyze multivariate data. It combines two different approaches: in a first step, a clustering algorithm is used to detect non-stationary spatiotemporal segments in the data (Hutt et al., 2000; Hutt and Kruggel, 2001; Hutt, 2001), while a subsequent step aims at modelling these signal segments mathematically by nonlinear dynamical systems (Hutt et al., 1999, Hutt and Kruggel, 2001, Hutt 2001). Applying the method to ERP- and MLAEP-data, components are detected objectively and the component P30 in MLAEP-data is modeled by a two-dimensional dynamical system (Hutt, 2001). The basic hypothesis of the presented work is underlying neuronal dynamics showing co-operative behaviour. It turns out, that cognitive components represent ordered and low-dimen-sional dynamical states, while transitions in between appear unordered and high-dimensional (Hutt, 2001).

Method

Multi-channel ERP- and ERF-data can be visualized as temporal sequences of spatial topographic maps, as shown in Fig.1 .

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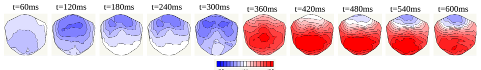

It is well-known (e.g. Brandeis et al., 1995), that quasi-stable intensity maps occur, which are approached and left in time. The presented work interprets this non-stationary behaviour as attraction and repelling by dynamical fixed points (Uhl et al., 1998). This behaviour is sketched in Fig.2 in a two-dimensional data space.

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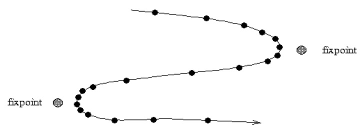

Attractions due to existing stable manifolds lead to increases of data point density near fixed points. Therefore, regions in data space showing increased point densities might result from attractive and repelling fixed points.

K - Means

Examining this hypothesis, the k-means cluster algorithm (Duda and Hart, 1973) is applied to multi-channel datasets. K-means determines an *a priori* fixed number of cluster centers, which are points in data space and thus represent intensity maps. In order to visualize the obtained clustering results, the Euclidean distance from each data point to each detected cluster center is plotted. Thus, we can follow the signal through the high-dimensional space and the resting states and transition parts become visible. At first, clustering results are dependant on the number of clusters. Therefore, a measure G(t) for the validity of cluster results is used (Hutt and Kruggel, 2001) which represents the probability that data is clustered at a timepoint t .

Experiments

Visual Experiment

In a first application, subject-averaged ERP data obtained from a visual experiment (Herrmann et al., 1999) is analyzed. Subjects were shown four visual stimuli (see Fig.3) in randomized sequence with equal probability of appearance.

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Two of them represent Kanizsa-figures and the subjects were asked to count the appearance of the square-figure. EEG-data is obtained by 60 channels at a sampling rate of 500Hz. ERPs are calculated by averaging over 10 subject and performed 400 trials of each subject. In Fig. 4, the temporal sequence of topographic maps for the target condition is shown.

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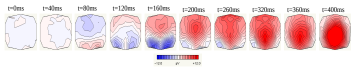

Figure 5 shows cluster results for data of the target condition for six clusters . A visual comparison of obtained clusters and known components shows good accordance. The known components are determined by peak-detection in single channels (Herrmann et al., 1999).

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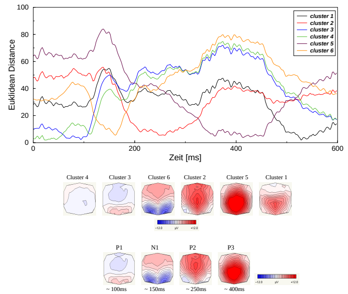

Since the choice of numbers of clusters is arbitrary up to this point of the method, the validity measure G(t) is calculated. In Fig.6 and 7, G(t) is plotted in respect to time for different time windows. Mountains of G(t) indicate clustered data, while valleys indicate parts in between clustered data. Calculating averages of data in clustered time windows leads to topographic maps. It turns out that they are equivalent to the cluster centers, shown in Fig.3. A substructure of the P300 is detected (Fig. 7).

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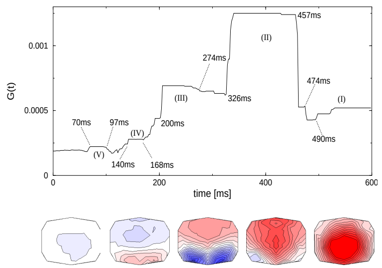

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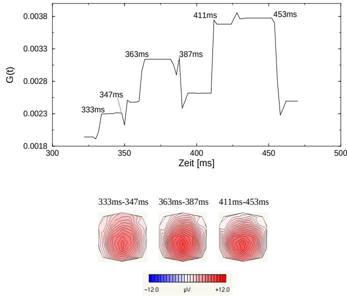

Middle Latency Auditory Evoked Potentials

Now, the clustering is applied to middle latency evoked potentials. Subjects heard a click of 100µs duration, while 32-channel EEG was recorded (Riedel and Kollmeier, 2000). A sampling rate of 10.000 Hz leads to a good temporal resolution.

Figure 8 shows (a) evoked potentials at electrode CP5 (10-20 system) and (b) the temporal sequence of topographic maps of a single subject.

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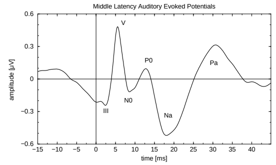

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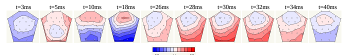

Results from the cluster validity check are shown in Fig.9. Latencies of obtained mountains and valleys show good accordance with waves and transition parts in the single channel data (Fig.8).

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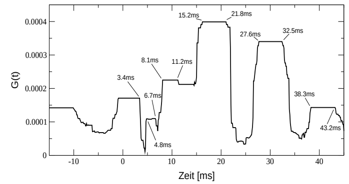

Focussing on the time interval [26ms; 33ms] of component Pa, a two-dimensional dynamical model is found by a nonlinear analysis method (Hutt et al., 1999), which synchronously fits a low-dimensional set of ordinary differential equations and spatial maps.

Projections of the high-dimensional signal onto two determined spatial modes are possible with 98% signalfit, shown in Fig.10. The originally motivated fixed points are obtained and shown in Fig.11: two sad-dle points and one stable focus are found.

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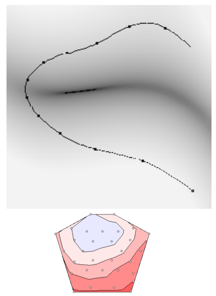

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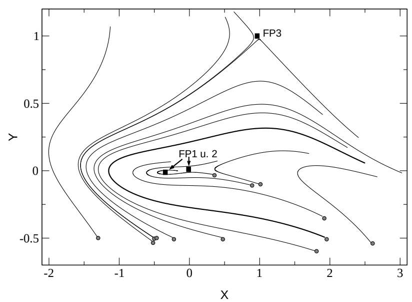

Conclusion

The presented work introduces a cluster method to detect functional components in spatiotemporal signals and applies a nonlinear analysis method to determine their spatiotemporal dynamics. Subject-averaged ERP- and MLAEP-data are analyzed and functional segments are detected. Comparisons of these segments and components determined by conventional methods (as peak-detection in single channels) show good accordance. This fact reveals the dynamical and functional character of ERP-components: low-dimensional spatiotemporal behaviour and ordered brain states, high-dimensional non-functional transitions between components. A similar procedure for the detection of components is developed by Pascal-Marqui et al. (1995). It determines so-called microstates (Brandeis et al., 1995) also by a k-means clustering, but without a criterion for the number of clusters. But the notion of microstates corresponds to the presented idea of dynamical states in the brain. The present approach implies and extends the microstates method, since they are based on similar assumptions about neuronal dynamics.

Reverences

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