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Global Visualization of Neural Dynamics

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Abstract. Non-linear mapping technique for global visualization and dimensionality reduction of high-dimensional signals (EEG, MEG, fMRI or neurodynamics) has been proposed. In contrast to commonly used decomposition techniques that try to discover interesting components, global visualization of high-dimensional trajectories shows various aspects of signals that are difficult to notice looking at individual components, or to follow looking at dynamical visualizations. The mapping used here is based on the Fuzzy Symbolic Dynamics (FSD) and can be applied to raw signals, transformed signals (for example, ICA components), or time-frequency signals. As an example visualization of the output layer (50 neurons) of a neural Respiratory Rhythm Generator model (RRG) that includes 300 spiking neural units is shown.

Keywords: Dynamical System, Symbolic Dynamics, Visualization of Signals, Dimensionality Reduction

1. Introduction

Understanding biomedical signals requires analysis of large high-dimensional data that changes in time. Popular techniques include decomposition of such data into meaningful components, using Principal Component Analysis (PCA), Independent Component Analysis (ICA), Fourier or Wavelet Transforms etc. Interesting events are then searched for in single components or correlations between them, with time-frequency-intensity colored maps showing how the processes unfold. Such techniques are very useful but do not show global properties of the processes in the high-dimensional signal space. For brain-computer interfaces and other applications a static snapshot of the whole trajectory, showing its main characteristics, could be very useful. One way to achieve it is to place in the signal space localized functions that are activated in a different way by the trajectories that pass near their center (an alternative is to define reference points and measure distance of the trajectory from these points using some metric). Using *k* such functions strategically placed in important points of the signal space a non-linear reduction of dimensionality suitable for visualization is achieved. This study is focused on mapping techniques that capture interesting properties of trajectories and relate them to the sources.

2. Material and Methods

Assume that some unknown sources create a complex multi-dimensional signal that is changing over time $x(t) = \{x_i(t)\}, i = 1..n, t = 0, 1, 2\ldots$, for example an EEG signal measured by n electrodes. Vector $x(t)$ form a trajectory in the signal space. Recurrence maps and other techniques are used to view this trajectory but do not capture many important properties that it reflects. In the symbolic dynamics the signal space is divided into regions that emit different symbols every time the trajectory is found in one of the regions. In the fuzzy symbolic dynamics membership functions are used instead of discrete symbols, with centers $\mu_1, \mu_2, \ldots$ of the regions in the signal space determined by some clustering algorithm. For example, two or more Gaussian membership functions:

$$y_k(t) = \exp\left(-\left(x(t)-\mu_k\right)^{\mathrm{T}} \Sigma_k^{-1} \left(x(t)-\mu_k\right)\right), \quad (1)$$

with diagonal dispersions Σ_k, will allow to map $x(t)$ to a lower-dimensional $y(t)$. If all Gaussian components have the same weights a single parameter defines dispersion. For each pair of functions their dispersions σ_1 and σ_2 should be sufficiently large to cover the space between them, for example:

$$\sigma_1 = \sigma_2 = \tfrac{1}{2} \| \mu_1 - \mu_2 \| . \quad (2)$$

If the goal is to distinguish several experimental conditions optimization of parameters of membership functions can be done using learning techniques to create clear differences in corresponding maps. Adding more localized functions in some area where dynamics is complex will show fine structure of the trajectory. Interpretation of maps obtained for a mixture of artificial radial and linear wave sources will be reported, as well as some real applications.

3. Results

FSD has been used to study behavior of neural Respiratory Rhythm Generator model (RRG). The model consists of 300 spiking neurons (200 beaters, 50 bursters and 50 followers) [Butera et. al. 1999]. Below visualization of the followers (model output layer) is examined. A trajectory based on 19600 vectors (normalized in every dimension), each containing membrane potentials of 50 follower cells, covering about 20 spikes, is displayed below. Vector clusterization was done with the *k*-means algorithm for $k = 2$ (for larger *k* pairwise diagrams are used).

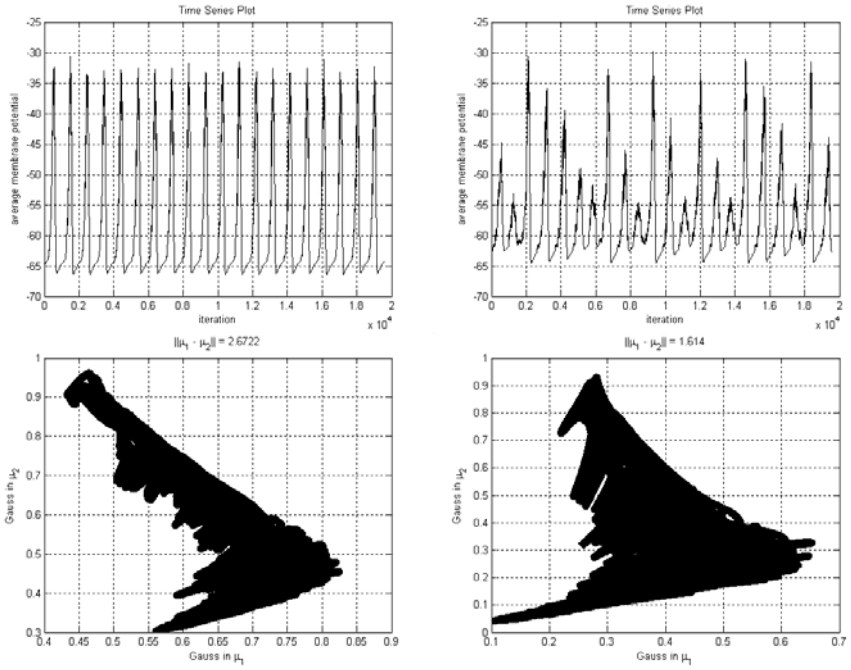

Figure 1. *Trajectory plots* (*bottom*) *done with thick pen for* 19600 *vectors containing membrane potentials of* 50 *follower cells from* RRG*, and time series plots* (*top*) *representing average membrane potential* (*sum of all potentials divided by the number of neurons*) *versus iteration number. Graphs on the left correspond to a normal rhythm case, and on the right to pathological one.*

4. Discussion

Although signals seem to be regular trajectories plotted with thick lines spread in the diagram making large blobs, indicating some irregularities. FSD mappings are sensitive to changes in phase relations of different components and differ strongly for normal and pathological cases. The parameters of FSD mapping may be learned in a supervised way from data, reducing or enhancing influence of some components of the signal, show strong differences in mappings for various experimental conditions. Thus the method should be quite useful in many applications, including brain-computer interfaces, especially in combination with traditional techniques based on component based analysis.

References

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