Dynamic Classification of EEG data

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MOTIVATION

The goal of this project is to develop methods to characterize neuronal ensemble dynamics from EEG data. The technique can be used to:

- Identify the EEG channels that primarily reflect the activity from a single source. The information can be used to perform source separation only on those channels that mostly reflect the activity from individual sources. This will aid in source separation.
- Obtain components of neuronal ensemble temporal dynamics that characterize the essential physical features of the activation mechnism.
- Differentiate brain responses in different experimental conditions based on the dynamic features of neuronal ensemble activity. This analysis provides information that is complementary to that found using standard ERP analysis and is likely to have 'higher differentiation power'.
- Test the quality of source separation. If the obtained sources do not show distinct dynamic components, in certain cases this can indicate that the sources were not well separated by the chosen source separation algorithm. This can be used to seek better source separation.
- Utilize the different temporal dynamic patterns of neuronal ensembles to classify neuronal sources.
- Reveal possible dynamic interactions between neuronal ensembles by identifying couplings in source dynamics models.
- Automatically classify and remove artifactual activity, for example ocular signals from the EEG data.
- Detect chaotic and non-chaotic states and the transitory states that can correlate with normal and abnormal brain activity, for example, to detect onset of epileptic seizures.

APPROACH

The technique we developed is based on models derived from Delayed Differential Equations (DDEs). These equations are used to describe the underlying dynamics of a wide class of physical processes. Such processes are typically characterized by a delayed reaction of some physical process(es) (see [1] for a list of examples).

Delayed Differential Equation (DDE) Models

Consider a discrete time series of length $n+1$, of some measured physical variable

$$x_0, x_1, \ldots, x_i, x_{i+1}, \ldots, x_n$$

whose underlying generating system is assumed to be governed by a dynamical system

$$\dot{x} = f(x, t)$$

which can be approximated by a polynomial expansion $f(x, \tau) = F(x, a)$,

$$\begin{aligned}
\frac{\mathrm{d}x}{\mathrm{d}t} &= a_0^0 + a_1^0 x + a_2^0 x_\tau + \cdots + a_i^0 x^2 + \ldots \\
\frac{\mathrm{d}x_\tau}{\mathrm{d}t} &= a_0^1 + a_1^1 x + a_2^1 x_\tau + \cdots + a_i^1 x^2 + \ldots \\
&\vdots
\end{aligned}$$

where $x_{m\tau} = x(t - m\tau); m = 0, 1, \ldots, D-1$ are D embedded variables.

One can estimate the coefficients of the polynomial model so as to minimize the distance between f and F.

We can achieve this by considering only a single delay equation, for example the first one above

$$\frac{\mathrm{d}x}{\mathrm{d}t} = a_0 + a_1 x + a_2 x_\tau + \cdots + a_i x^2 + ...$$

One delay is typically insufficient to characterize the dynamics of a system. A general multi-delay model is

$$\frac{\mathrm{d}x}{\mathrm{d}t} = a_0 + a_1 x + a_2 x_{\tau_1} + a_3 x_{\tau_2} + \cdots + a_i x^2 + a_{i+1} x x_{\tau_1} + ...$$

Our goal is to extract typical properties of the data rather than recover a model of the underlying dynamical system. For such a purpose simple models are sufficient. To this end, a simple two delay model [2, 3] is used predominately in practice

$$\dot{x} = a_1 x_{\tau_1} + a_2 x_{\tau_2} + a_2 x_{\tau_1} x_{\tau_2}.$$

To constrain the optimization problem further, the delays are set to some fixed values.

While the non-linear two-delay model has been shown to be a powerful tool for modeling dynamical processes, it is not optimal. When noise is present in data, the choice of parameters including time delay values, the number of delays, and the choice of model order, have a significant effect on the quality of the results. In this study we explore optimal DDE models for the EEG application.

NEW DELAY DIFFERENTIAL EQUATION MODELS

We developed a more general procedure for DDE modeling. We use a general DDE of the form

$$\dot{x} = a_1 x_{\tau_1} + a_2 x_{\tau_2} + a_3 x_{\tau_3} + \cdots + a_i x_{\tau_1}^2 + a_{i+1} x_{\tau_1} x_{\tau_2} + \ldots$$

where we parameterize the model coefficients and the time delays. We choose the number of delays, the order of non-linearity, and the number of maximal terms we would like in the model. The optimization to find parameters is done via two Genetic Algorithms (GAs), the delay selection GA and the model selection GA, which are run alternatively.

Application of Dynamic Classification to EEG data

The EEG and EOG data were collected while subjects were either visually following a geometric pattern displayed on a computer screen or while visually examining a picture of a human face also presented on the screen directly in front of them. In both cases the subjects' heads were immobilized so the subjects could only move their eyes in order to focus on the different parts of the screen. The data are a courtesy of Carrie Joyce from the UCSD Computer Science Department.

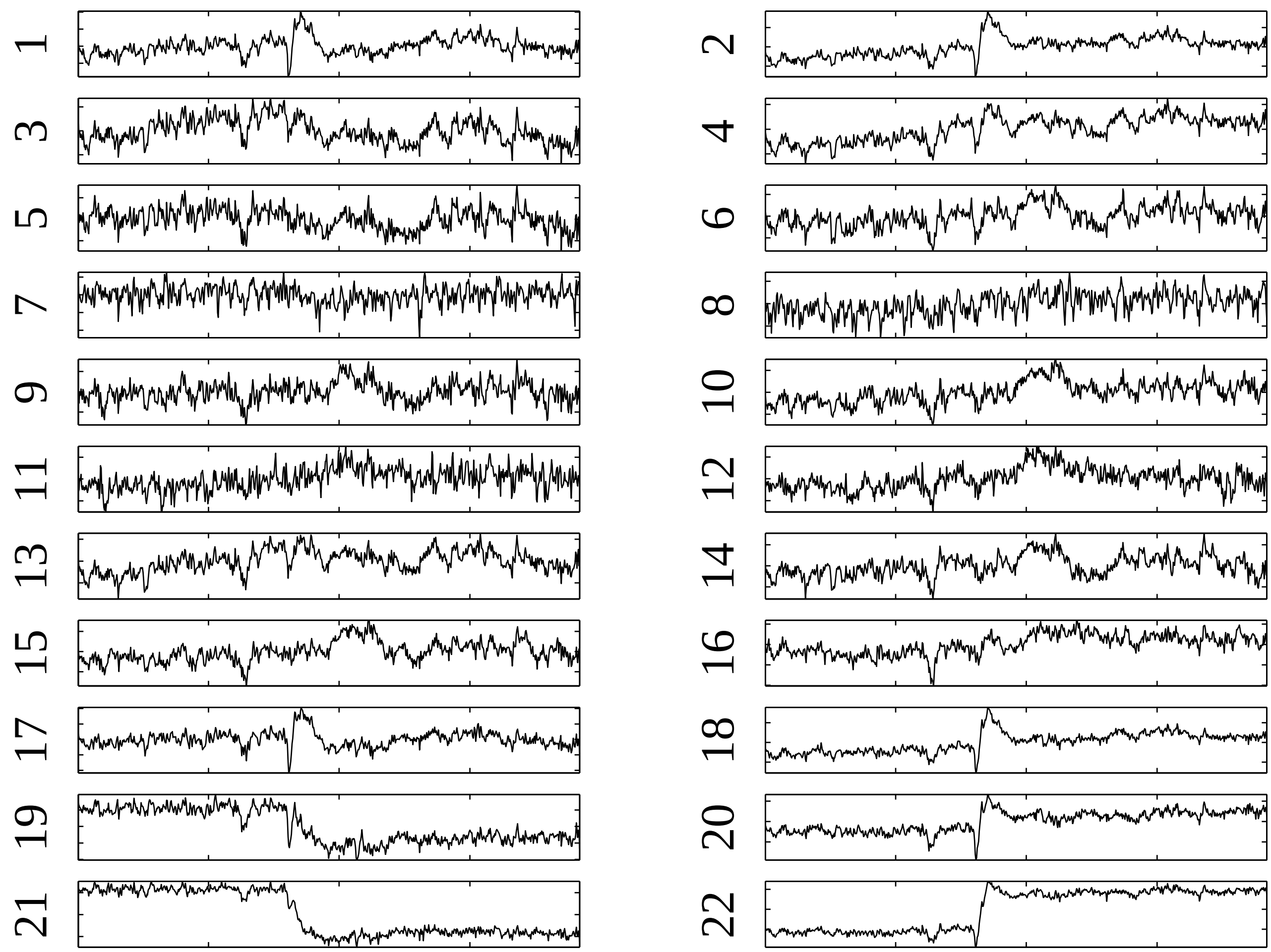

Figure 1: EEG and EOG recordings during tracking of a geometric pattern on a computer screen

channel #	abreviation	description
1	FP1	left prefrontal
2	FP2	right prefrontal
3	F3	left frontal
4	F4	right frontal
5	C3	left central
6	C4	right central
7	T3	left temporal
8	T4	right temporal
9	P3	left parietal
10	P4	right parietal
11	O1	left occipital

channel #	abreviation	description
12	O2	right occipital
13	Fz	midline frontal
14	Cz	midline central
15	Pz	midline parietal
16	A2	right mastoid
17	LU	left upper eye
18	RU	right upper eye
19	LL	left lower eye
20	RL	right lower eye
21	LH	left horizontal eye
22	RH	right horizontal eye

Source Separation

Source separation from raw data was performed using the Second Order Blind Separation Algorithm (SOBI) [4], shown in Figure 2.

The ocular components are clearly visible in the decomposition.

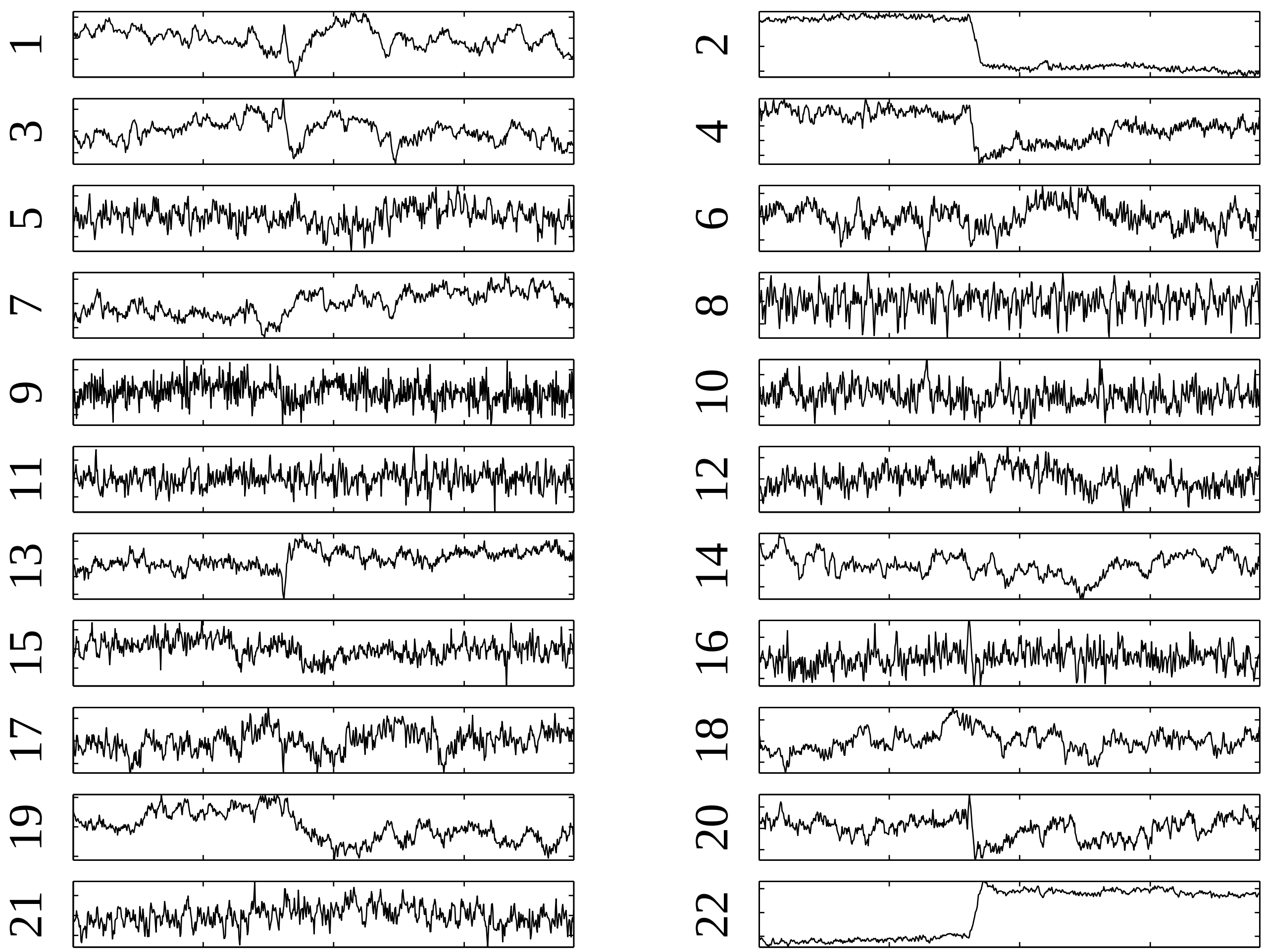

Figure 2: Separated Sources from data shown in Figure 1. Components 2 and 22 are the ocular sources.

From the general DDE model we identify model components which differentiate the source of interest. We apply our method to the sources separated using SOBI, shown in Figure 2.

We have found that ocular sources are best modeled by the coefficients $a_{1,2,3}$ of the DDE model

$$\dot{x} = a_1 x_{\tau_1}^2 + a_2 x_{\tau_1} x_{\tau_2} + a_3 x_{\tau_2}^2$$

Figure 3: Coefficient values for the models with the most significant delays found for each SOBI component shown in Figure 2 using above DDE model. The time lag values for two delays are listed on top of each square. Component number is listed on the Y-axis. Similarity in structure is evident for certain components, For example components 2 and 22 have similar structure and so do components 4, 7, 14, 20.

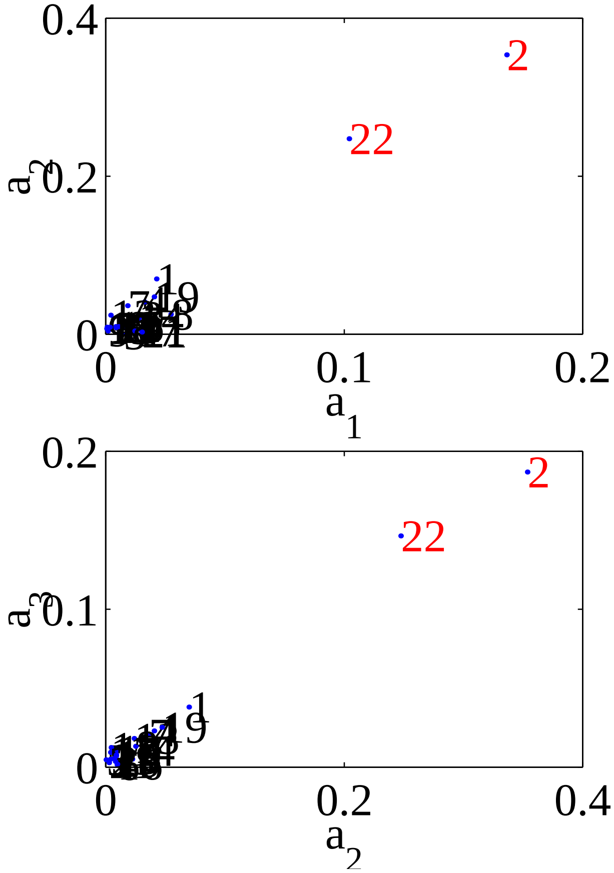

Figure 4: The coefficients $a_{1,2,3}$ for the best delay DDE model for each SOBI component. The ocular sources 2 and 22 are clearly identified and can be automatically removed from the data.

The standard two delay model

$$\dot{x} = a_1 x_{\tau_1} + a_2 x_{\tau_2} + a_2 x_{\tau_1} x_{\tau_2}$$

was found to be sensitive to a finer structures in the data. Figure 5 shows SOBI components sorted by the value of the a_1 coefficient estimated for this model.

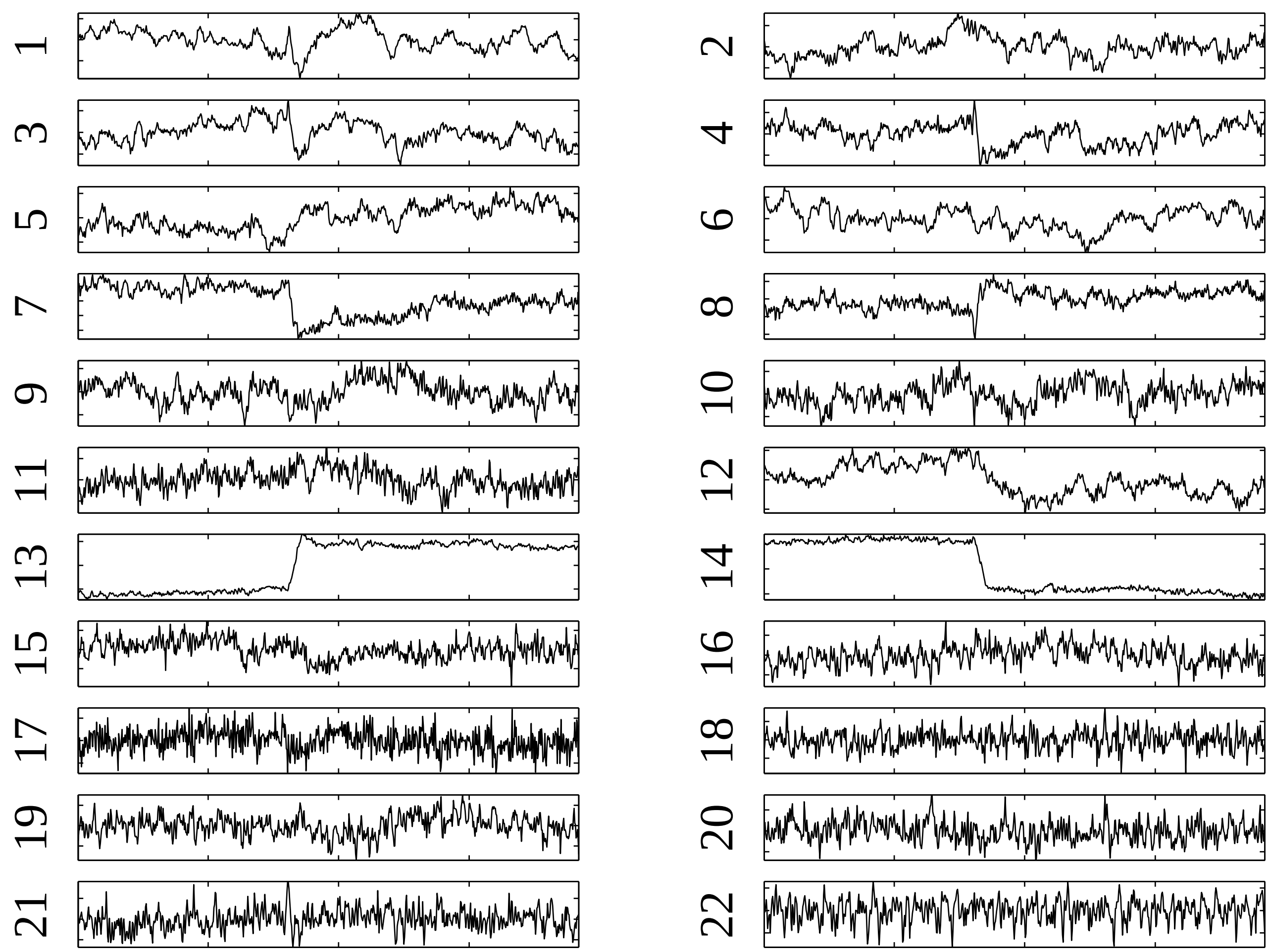

Figure 5: SOBI components sorted by ascending values of the a_1 coefficient

Note that this model identifies similarities in the gross temporal structure of the components.

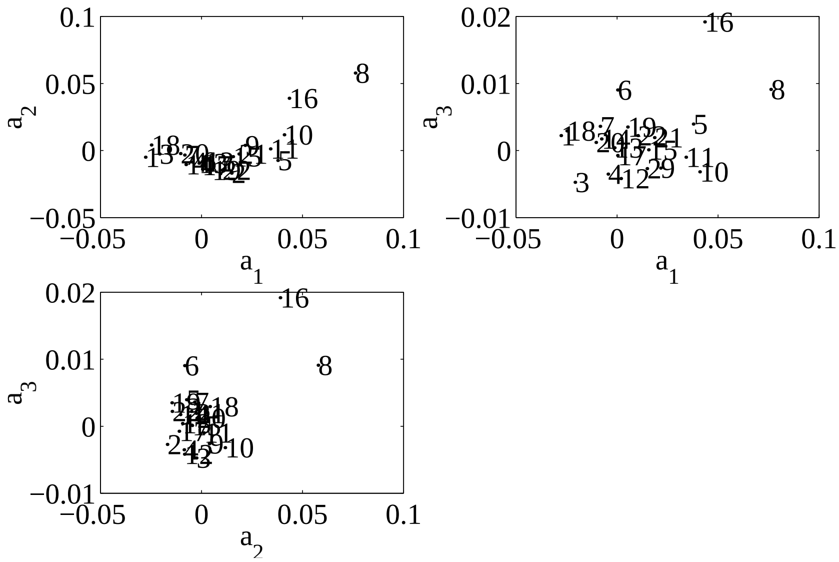

Figure 6: Distribution of the $a_{1,2,3}$ coefficients used to sort SOBI components above.

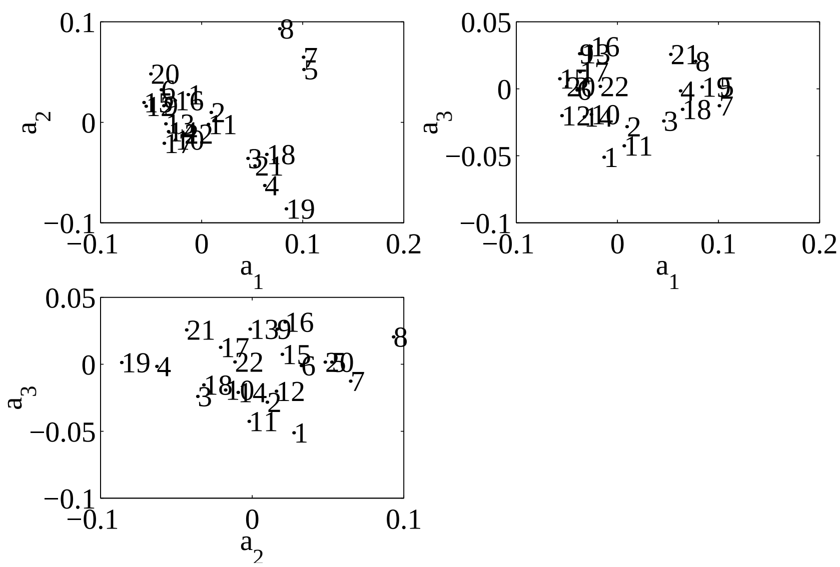

Figure 7: The same distributions as in Figure 6 for the data recorded while subject is viewing a face. Note the difference in the distribution of the coefficients between the two figures pointing to different excitation dynamics that arise in response to the two different tasks.

References

[1] R.D. Driver. *Ordinary and Delay Differential Equations*, volume 20 of *Applied Mathematical Sciences*. Springer-Verlag, 1977.

[2] J. Kadtke and M. Kremliovsky. Estimating dynamical models using generalized correlation functions. *Physics Letters A*, 260(3-4):203, 1999.

[3] J. Kadtke and A. Pentek. Automated signal classification using dynamical models and generalized higher-order data correlations. *USN Journal of Underwater Acoustics*, in press, 2000.

[4] A. Belouchrani, K. Abed Meraim, J.-F Cardoso, and E. Moulines. A blind source separation technique using second order statistics. *IEEE Trans. on SP*, 45:434–444, Feb. 1997.

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