A Novel Single-Trial Analysis Scheme for Characterizing the Presaccadic Brain Activity Based on a SON Representation

Konstantinos Bozas[1,*], Stavros I. Dimitriadis[1], Nikolaos A. Laskaris[1,*], and Areti Tzelepi[2]

[1] Laboratory of Artificial Intelligence & Information Analysis, Department of Informatics, Aristotle University of Thessaloniki, 54 124, Greece
konmpoz@gmail.com, stdimitr@csd.auth.gr, laskaris@aiia.csd.auth.gr
[2] ICCS, National Technical University of Athens, Greece
areti@iccs.gr

Abstract. We introduce a tactic for single-trial (ST) analysis that incorporates, in the study of saccades, the experimental control of a behavioural variable within the standard paradigm of a repeated execution of a single task. The ubiquitous ST-variability in brain imaging recordings is turned, here, to an additional informative dimension that can be exploited to gain further understanding of brain's function mechanisms.

Our approach builds over a self-organizing neural network (SON) that can efficiently learn and parameterise the variability in the patterning of electro-oculographic (EOG) signals. In a second stage, the STs of encephalographic activity are organized accordingly and the observed variations in the EOG signals are associated with specific brain activations. Finally, complex network analysis is employed as a means to characterize the ST-variability based on modes of functional connectivity.

Using EEG data from a Go/No-Go paradigm, we demonstrate that the spontaneous variations in the execution of a saccade can open a window on the role of different brain regions for ocular movements.

Keywords: EEG, EOG, Neural-Gas, phase-locking, network-metrics.

1 Introduction

There is nowadays a vast variety of experimental techniques applicable for studying the nervous system, based on diverse instrumentations, with which various brain theories can be brought under test. Usually, neuroscience research proceeds in either of the two following ways: i) the controlled experimental approach and ii) the empirical approach [1]. In the first case, an experiment is conducted for the purpose of determining the effect of a single variable of interest (like stimulus color) on a particular system. The influence of all other variables (attention, habituation etc.) is attempted to

* Corresponding author.

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kept at minimum via appropriate manipulations. On the other hand, the empirical method is based on the collection of a large amount of related data which need, later, to be processed efficiently and sorted accordingly. Data analysis needs to be adjusted not only with respect to the particular recording technique, but also with respect to either of the two experimental approaches. The spirit of regression dominates the analysis of data from controlled experiments, while the notion of classification (mostly in its unsupervised flavor) dominates the empirical studies.

Within the previous experimental manipulations, the extremely popular paradigm of event-related responses is included as well. A particular task (e.g. finger movement, target detection) is repeatedly performed by the subject with the aim of collecting sufficient number of relevant traces of brain activity. The recorded signals, after time-alignment, are processed by averaging so as to diminish the ongoing activity (including spontaneous brain activity) and reveal the task-related component of the signals. In principle, event-related paradigms belong to the category of controlled experiments. However, a thorough study of (a large collection of) actual data can demonstrate the phenomenon of *'ST-variability'*, which is usually attributed to the non-stationary character of brain and calls for adopting methodologies designed for analyzing data from empirical studies. In a series of previous publications [2]-[5], we experimented with the idea that ST-variability can be treated as a useful signal. The justification was based on the simplest experimental set-up, this of collecting multiple ST-responses during identical sensory stimulation in humans. We have therefore introduced suitable signal-analytic algorithms to manipulate the involved variations in order to gain insights into the brain mechanisms and probe functional associations between different brain areas. In the present study we extend the above consideration in the case of event-related responses, by introducing the concept that the (originally) unduly variations in the performance of a task can be exploited in order to test the role of different brain activations.

Saccade-related activity has been explored in many previous neuroscientific studies [6]-[9], with the involved experiments adopting both the empirical and controlled experimental approaches. It is the scope of this work to introduce a hybrid methodology that works with saccade-related data from a standard EEG experiment where the subject had to execute the movement as fast as possible. First, the EOG signals are grouped, by means of Neural-Gas network, according to the velocity patterning of the executed movement. This partition (into slow, fast and very-fast movements) is then transferred to brain signals in order to detect the temporal modulations of a complex scheme with which the brain controls the response to the external stimulus (the visual cue for the movement). Finally, functionally connectivity analysis is performed - independently for each group of STs- based on a *phase-locking* estimator that associates a functional dependence value to every edge in a graph built over all the placed electrodes.

The rest of the paper is structured as follows. Section 2 has an introductory purpose and reviews shortly well-established knowledge about presaccadic brain activity. Section 3 includes a short description of the available data. Section 4 provides a detailed description of our methodology and Section 5 reports on the new experimental findings.

2 Background

Preparing a movement is a complex process. It involves different sensory-motor transformations in the human brain before the movement is finally executed. There has been extensive research of how the central nervous system controls voluntary action. Although today we have a reasonable understanding of the different stages involved in this complex process, some aspects are still not clear. In order to perform a movement, position and the velocity vector (including direction and speed) need to be calculated. Previous research [10] on the encoding of kinematic parameters in the motor cortex while primates performed arm movements showed a direct relationship between kinematics and neural activity over the motor cortex. Many studies later on have confirmed these findings and revealed new aspects of this relationship. However, little is known about the relationship of brain activity to the kinematics of eye movements. We know from previous EEG studies that brain activity preceding an eye movement is similar to the one preceding finger movements [11],[12]. Here, we examine the dependence of saccade velocity on preceding brain activity as recorded with EEG.

3 Experimental Data

3.1 Experiment Description

In order to explore the relationship between EEG activity and saccadic eye movement, a Go/No-Go experimental design was adopted (See Fig.1). According to the color of the fixation cross, the subject had either to make a saccade (green cross), or ignore (red cross) the lateral target and keep fixating at the center. In the beginning of a trial, a white cross comes on. Then the color of the cross changes (red/green) and at the same time a lateral target (left/right) appears. The subject has to keep fixation on the colored cross. When the color of the cross becomes white again (Go signal), the subject has to make a saccade to the target if the color of the cross was green, or keep fixation ignoring the target otherwise (i.e. in case of a red cross). The last frame (empty frame) provides a relaxation period during which the subject can blink, rest, etc.

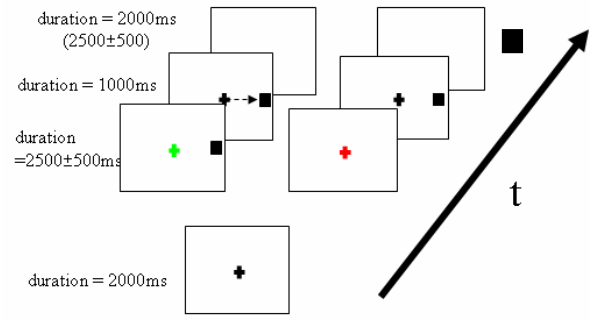

Fig. 1. The different periods in the time course of a single trial

Every subject attended 7 to 9 runs and each run consisted of 40 trials. (20 for Go, 20 for No-Go condition). The duration of each trial was 8 seconds. The EEG signals were recorded via 64 electrodes, which were placed according to the international 10-20 electrode position classification system. The EOG signals were simultaneously recorded through two pairs of electrodes attached to the top-bottom side and right-left side of the right eye (vertical and horizontal EOG). All data were sampled at 1024Hz.

3.2 EEG Processing and Artifact Rejection

The raw EEG data were filtered by a high-pass filter (cut-off 0.16Hz) and by a low-pass filter (cut-off 100 Hz). The data were further processed so as to, first, remove 'outlying' trials and, then to enhance the SNR in the remaining ones. Since oculographic noise was prevalent in our EEG data (due to the nature of the experiment), we applied the recently introduced (a simple, robust and fully automatic technique) *regression-based EOG reduction method* [13], which suppresses the fast and slow EOG-related artifacts of the multichannel EEG data.

4 Methodology

A flowchart of the (main steps of the) introduced methodology is provided in Fig.2. In a nutshell, *Neural-Gas* algorithm splits the EEG STs into different groups based on the corresponding velocity profiles of the EOG-signals. For each group, we measure (across trials) the *phase locking value* for every possible pair of EEG channels. In this way a graph representation of brain-connectivity is formed, in which nodes corresponds to electrodes. The obtained graph is characterized via a *local network metric*, which expresses the segregation and evaluates communication efficiency among the nodes. This characterization is repeated for different time segments of EEG data, and presented in a time-dependent topographic format that facilitates the recognition of brain regions with activation that relates causally with the forthcoming saccade.

4.1 Saccadic Onset Detection and ST-Data Collection

In order to extract segments of brain activity related with the saccade initiation, the saccadic movement onset had to be, first, detected based on the horizontal EOG signal. *Position-variance* and *velocity-based methods* [14] are among the most popular techniques, utilizing the sharp increase/decrease of the EOG signal during eye movement. Marple-Horvat et al. [15] suggested a technique with a linked double window applied to an approximation of the first derivative of the EOG position, which yielded fine identification rates to our data and therefore adopted in this study.

Since the above onset detection technique, occasionally, produced false positives, we incorporated an outlier-detection step just after the onset detection. Based on the onset latencies, a set of EOG signal-segments were first extracted and then fed to an artifact rejection technique [16]. This technique uses signal morphology to compare every segment against each other and then realizes reduced-ordering of the involved EOG-patterns in order to enable the removal of outliers (i.e. segment wrongly recognized as containing saccadic onset). The remaining EOG-segments formed the ensemble of EOG-STs. The corresponding EEG-segments, extracted from the concurrently recorded multichannel signal, formed the ensemble of EEG-STs.

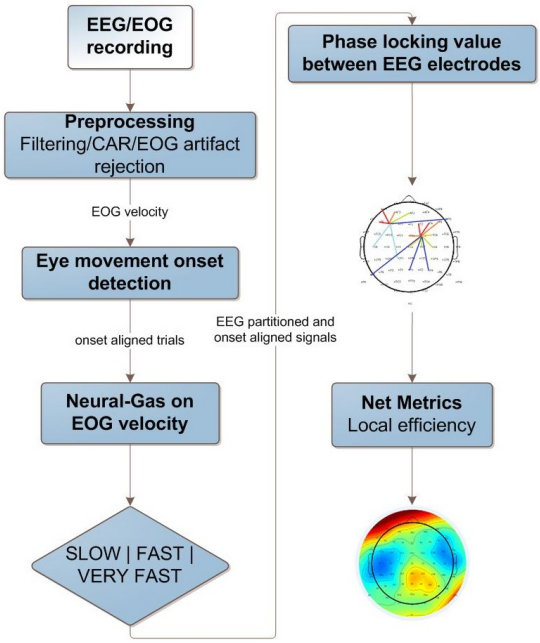

Fig. 2. Flowchart of the main steps

4.2 Grouping STs with Neural-Gas acting on EOG-Velocity Patterns

In an attempt to link the behavioral response (saccade) with the initiating brain activity, we treat the EOG-segments (from the saccade onset and before) as a set of multivariate patterns. The inherent variations in this set are leaned by means of Neural-Gas network and parameterized in a parsimonious and intelligible way. This included the formation of different groups of EOG-segments, which are sorted according to relevant semantics (that are of interest for the particular study of presaccadic brain activity). Having in mind that oculographic signals are indicative about the velocity of a saccade, we choose to associate with the EOG-segments the corresponding velocity patterns. This can be thought as a feature-extraction step, with which the subsequent learning algorithm is guided to focus on the important aspects of EOG variations. Hence, the N segments of EOG-signals are associated with $\{X_i\}$, i=1,2,…N , i.e. with vectors having as coordinates the estimates of saccade velocity at successive latencies (before the detected onset).

Neural-Gas network is then employed to accomplish the learning task, i.e. to organize the saccades based on their velocity profiles. This algorithm is an artificial neural network model, which converges efficiently to a small, user-defined number $k<N$ of codebook vectors, using a stochastic gradient descent procedure with a "soft-max" adaptation rule that minimizes the average distortion error [17]. Following the procedure described in [3], the computed code vectors are then assigned ranks based on their MST graph. Finally, the ordered code vectors $O_j \in \Re^p \; j = 1,2,...,k$ were used in a simple encoding scheme: the nearest code vector was assigned to each X_i. This procedure divides the data manifold $V \in R^p$ into k Voronoi-regions.

$$\mathbf{V}_j = \{X \in \mathbf{V} : \|X - O_j\| \leq \|X - O_i\| \forall i, i = 1,2,...,k \cdot \tag{1}$$

From a more practical point of view, the bulk of information contained in the data is represented, in a parsimonious way, by a (Nxk) partition matrix U, with elements u_{ij} such that

$$u_{ij} = \begin{cases} 1 & if\ X_i \in V_j \\ 0 & if\ X_i \notin V_j \end{cases}, \sum_k^j \sum_{i=1}^N u_{ij} = N \cdot \tag{2}$$

The derived grouping (estimated for EOG-signals) is applied to the corresponding EEG-STs. In this way, groups of multichannel data are emerging which can be compared in order to understand what was the leading cause of the observed variability (i.e. in the patterning of saccade velocity).

The previous steps are exemplified, via Fig.3, in the case of a subject with 58 trials of left saccades. Neural-Gas algorithm was executed using the approximation of the first derivative of the EOG signal (previously used for detecting the onset [15]). The input vectors consisted of 100 samples before the movement onset and 100 after it. Using k=3, we ended up with three groups (containing 18,14,26 trials respectively), which can easily identified as *SLOW, FAST and VERY FAST* saccades (see Fig.3a). By grouping the EEG-STs accordingly and deriving within-group averages, we can provide prototypes of brain activation (see Fig.3b).

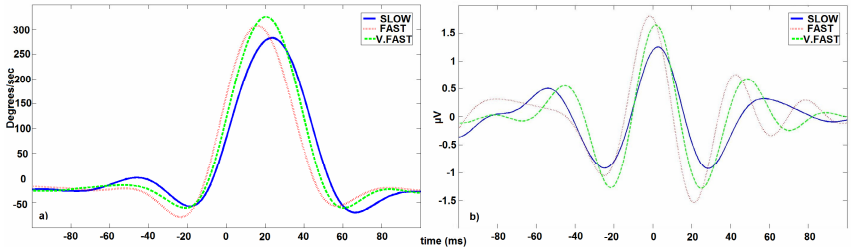

Fig. 3. a) Codebook vectors for left saccade velocity profiles. b) Prototypical EEG activity (in beta band), recorded at C2 electrode, for each saccade group.

4.3 Between-Groups Comparison of Brain Dynamics

With the scope of identifying the leading causes of the observed variation in behavior, the k-groups of EEG-STs can be contrasted for time-intervals well before the saccade onset. There is a multitude of methods with which the spatiotemporal brain dynamics can be compared based on the corresponding ST-segments of multichannel EEG-data. Spectral characterization, topography of signal activations, event-related synchronization/desynchronization (ERS/ERD) are the most popular approaches to proceed with. However, after experimenting with them, we realized that the most striking between-groups explanations could be provided via a *complex-network approach*, which emphasized neural synchrony and is summarized as follows

(i) First, an estimator of phase synchrony (known as *Phase Locking Value* (PLV) [18]) is applied (using signals filtered within a particular frequency band) to every possible pair of electrodes and for different time windows. The computed estimates were tabulated, for each group of STs independently, in time-series of [64x64] matrices (in which an entry conveys the strength of functional connection between a particular electrode pair). Such a matrix has a natural graph representation, called hereafter as functional connectivity graph (FCG), with nodes being the recording sites and edges the in-between links weighted by the tabulated values. The *PLV* was employed successively between 150ms before the eye movement onset and 25ms after it with a time window of 50ms and 5ms time step, producing 25 *FCG* snapshots in total.
(ii) Each of the formed FCGs is then characterized based on a network metric called *local efficiency.*
(iii) Finally, The k groups of EEG-STs are compared -in a time dependent manner- regarding network-properties.

The employed *PLV* is known to quantify the frequency-specific synchronization between two neuroelectric signals. Hence, with the adopted procedure the role of neural synchrony (as a putative mechanism for long-range neural integration) is explored during saccade planning till movement initiation. For each trial n, n=1 ,..., N_k, (in the k-th group) the phase $\varphi(t,n)$ is extracted for all latencies *t.* The *phase locking value (PLV)* is defined at time instant *t* as the average value:

$$PLV_t = \frac{1}{N_k}\left|\sum_{n=1}^{N_k} exp(\, j\theta(t,n))\right| . \tag{3}$$

where $\theta(t, n)$ is the phase difference $\varphi_1(t, n) - \varphi_2(t, n)$ between the signals (filtered within a particular frequency range) corresponding to a pair of electrodes. PLV measures the inter-trial variability of this phase difference at t. If the phase difference varies little across the trials, PLV is close to 1; otherwise is close to 0. Usually, the above quantity is integrated over successive latencies so as to achieve a more robust measurement. In our implementation, the EEG signals are filtered within known frequency bands (e.g. α-waves, γ-oscillations) and the latency-dependent PLV values are averaged over particular time periods before using them as weights for the FCGs.

To characterize each FCG, we measure its *local efficiency* [19]. This metric is known to express how efficiently information is exchanged over the network. By using efficiency, brain neural network is seen as system that is both globally and locally efficient. The local efficiency E_{loc} reveals how much the system is fault tolerant, thus it shows how efficient the communication is between the first neighbors of *i* when *i* is removed:

We can characterize the local properties of *FCG* by evaluating for each vertex *i* the efficiency of its $\mathbf{G}_i$, the subgraph of the neighbors of *i*. We define the *local efficiency* as the average of all individual efficiencies:

$$E_{loc} = \frac{1}{M}\sum_{i\in M}\frac{\sum_{j,h\in \mathbf{G}_i,\, j,h\neq i}(d_{jh})^{-1}}{k_i(k_i-1)} . \tag{4}$$

where k_i corresponds to the total number of neighbors of the current node, M is the set of all nodes in the network and *d* keeps the shortest absolute path length between every possible pair in the neighborhood of the current node.

5 Results

Our experimentations with the previously described characterization of frequency-dependent, time-varying functional connectivity graphs, revealed that *Beta band (13-30Hz)* was the frequency channel that provided the best explanation about the formation of different saccades-groups (slow, fast, very fast). This finding fits well with the widely-known involvement of high-frequency EEG activations during saccade generation [7],[8],[20].

The visualization of the results, as a time-series of topographic maps, from the network analysis (restricted within beta-band) enabled us to track differences during the generation of different groups of saccades and draw conclusions about the local exchange of information in a time-dependent manner (See Fig. 4). These snapshots of brain connectivity clearly indicate that brain's self-organization tendencies should be pursuit within the domain of inter-areal interactions as well (i.e. apart of the signal domain). The thorough examination of the topographies included in Fig.4 facilitates the following observations.

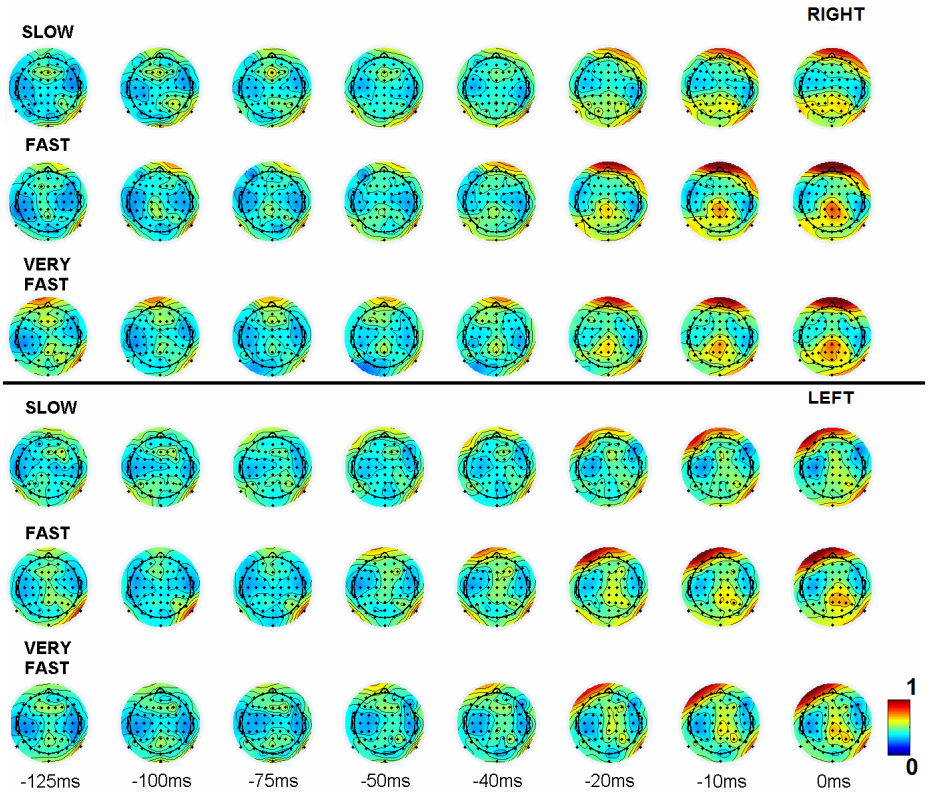

Fig. 4. Successive topographies of channelwise local network efficiency ($\mathbf{G_i}$) during preparation for right/left saccade (up/down). Time 0 ms corresponds to saccade onset.

In both left and right saccade, there is contralateral activity emerging before the eye movement onset (0ms) in centro-parietal, parietal and occipital brain areas. The results suggest that brain activity just before a saccade is modulated by saccade velocity. The differences were located mainly over parietal cortex. It is well known that posterior parietal cortex is a crucial interface between the motor and perceptual system in mediating sensory-motor transformations [8]. An eye-movement related region within the intraparietal sulcus (IPS) of the posterior parietal cortex sometimes referred to as the "parietal eye filed".

Of great importance is the inter-group comparison that reveals temporal differences following the grouping of saccades according to velocity. In *SLOW* saccades, information exchange begins -10ms before onset, while in *FAST* and *VERY FAST* saccades, starts earlier (-50ms). Interestingly, in the case of *VERY FAST* saccades, this exchange is apparently greater.

6 Conclusions

We have introduced a ST-analysis framework for characterizing brain's self-organization in terms of functional connectivity and network properties during the execution of saccades. It can offer novel knowledge about the coding of kinematic parameters related to eye movements. Neural-gas recognizes the different variations of the performed task and network analysis provides their explanations. The methodology is applicable to other cognitive tasks as well, while can be further advanced via affirmative randomization tests. Furthermore, it can be used to study the neural activity related to the kinematics of arm movements in order to drive neural prostheses.

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