Detection of Eye Movement Characteristics Using Reservoir Computing in High-Noise Environments

Nikita Brusinskii
Baltic Center for Neurotechnology and Artificial Intelligence
Immanuel Kant Baltic Federal University
Kaliningrad, Russia
nikita@brusinskii.ru

Vladimir Antipov
Baltic Center for Neurotechnology and Artificial Intelligence
Immanuel Kant Baltic Federal University
Kaliningrad, Russia
VMAntipov@kantiana.ru

Artem Badarin
Baltic Center for Neurotechnology and Artificial Intelligence
Immanuel Kant Baltic Federal University
Kaliningrad, Russia
Badarin.a.a@mail.ru

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***Abstract*—Accurate real-time detection of saccades is crucial in neuroscience but challenging under high noise levels. We introduce a model based on reservoir computing and tested on simulated eye movement signals with varying 1/f noise. The model achieved 99.5% accuracy without noise and maintained over 90% accuracy even at high noise levels, demonstrating its noise resistance and suitability for real-time brain-computer interfaces.**

***Index Terms*—reservoir computing, EyeTraking, machine learning, saccads**

I. Introduction

One of the key tasks of modern neuroscience is the study of brain mechanisms and related psychophysiological processes [1]–[6]. In neuroscience, oculography stands out as one of the most important tools, as it allows for the analysis of eye movements during the perception and processing of visual information [7], [8]. Since oculomotor activity is closely related to cognitive processes such as attention, memory, and the analysis of visual stimuli, its study is extremely important for understanding brain function as a whole [9].

Traditionally, eye movements are divided into two main phases—saccades and fixations. Saccades, which are rapid eye movements between fixation points, play a key role in visual perception. However, accurate detection of saccades in real time is especially difficult under high noise levels, complicating the analysis of oculomotor activity [10]. In such situations, the accuracy of recording and processing eye movements is critically important, as it minimizes the impact of artifacts and provides reliable data for subsequent research.

To overcome these difficulties and reduce hardware requirements, we are developing an algorithm for detecting eye movements in real time using reservoir computing (RC). RC has already proven to be an effective tool in a number of tasks related to signal analysis under noisy conditions [11]. Due to its ability to efficiently process complex temporal sequences of data [12], [13], RC appears to be a promising method for analyzing oculomotor activity in real time.

Thus, the main purpose of this work is to develop and apply an algorithm for the accurate determination of oculomotor activity in real time using reservoir computing.

II. Methods

The developed saccade detection algorithm based on reservoir computing was tested on a simulated oculographic signal. Simulating the oculographic signal is necessary because manual classification of oculographic data does not always yield reliable results due to the influence of various factors [14]. Moreover, the simulated signal provides full control over all examined characteristics, such as the number, amplitudes, and durations of saccades and fixations. The simulated signal is based on the model proposed by Richard Schweitzer and colleagues [15], incorporating different levels of noise. The choice of the model proposed by Schweitzer for simulating the oculographic signal, specifically the horizontal and vertical components, is due to its ability to generate post-saccadic oscillations, making the data more relevant to real-world signals. Additionally, the eye movement simulation model used allows for the modeling of fixation drift (tremor, microsaccades), further aligning the simulated signal with real oculographic data [16]. The noise used in the simulation was $1/f$ (flicker) RMS noise [17]. Various levels of RMS noise enable the study of how noise affects detection accuracy and help identify the limits of algorithm performance in the presence of significant data distortions. Using the model described above, 150 consecutive saccades and fixations were generated with varying levels of flicker noise. In this study, post-saccadic oscillations were not considered.

Simulated eye movements were fed to the input of a reservoir based on nonlinear vector autoregression and proposed in [18]. The task of the RC was to classify the time

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series, namely to perform a binary classification to distinguish between fixations and saccades. Thus, a step function was used as the target function, where the value 1 corresponded to the saccade, and the value 0 corresponded to the fixation (see fig. 1a). Additionally, we applied threshold filtering to the reservoir output: values above 0.5 were assigned a value of 1, and values below 0.5 were assigned a value of 0.

III. Results

First, we ensured that our proposed model for classifying eye movements is effective. To achieve this, we optimized the hyperparameters of the reservoir using noise-free simulated data (see Fig. 1a). The optimal parameters were a quadratic nonlinearity, 25 delays each with a duration of 3. Figure 1a shows the temporal realizations of eye movements; the dotted line corresponds to the data labels, and the solid line represents the results of the model classification. It is clear to see that the proposed model successfully performs the task of classifying eye movements. The accuracy was calculated as the proportion of correctly classified points, which was 99.5% for the specified parameters.

After that, the effect of noise on accuracy was investigated. Various noise levels ranging from 0 to 100 were considered, and it was found that even at high noise levels, the accuracy remained above 90%.

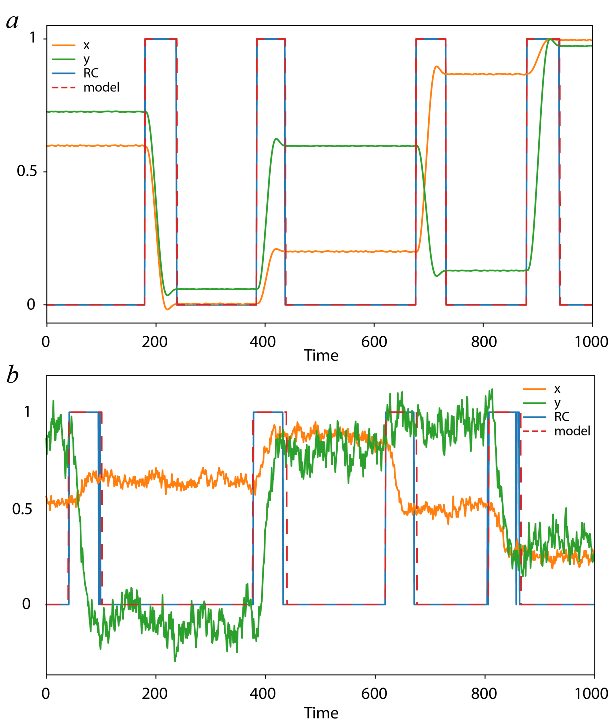

Fig. 1. Temporal realizations of eye movements: Figure (a) corresponds to a noise-free implementation, while figure (b) corresponds to an implementation with noise where the RMS value equals 100. The dotted line represents the data labels, and the solid line shows the results of model classification.

IV. Conclusion

Thus, the proposed model based on next-generation reservoir computing is resistant to noise and allows for the detection of saccades with high accuracy and low latency, making it suitable for use in real-time brain-computer interfaces.

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