A Blind Source Separation Algorithm for the Processing and Classification of Electro-oculogram Data

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Abstract. Abnormalities in the oculomotor system are well known clinical symptoms in patients of several neurodegenerative diseases, including modifications in latency, peak velocity, and deviation in saccadic movements, causing changes in the waveform of the patient response. The changes in the morphology waveform suggest a higher degree of statistic independence in sick patients when compared to healthy individuals regarding the patient response to the visual saccadic stimulus modeled by means of digital generated saccade waveforms. The electro-oculogram records of six patients diagnosed with ataxia SCA2 (a neurodegenerative hereditary disease) and six healthy subjects used as control were processed to extract saccades. We propose the application of a blind source separation algorithm (or independent component analysis algorithm) in order to find significant differences in the obtained estimations between healthy and sick subjects. These results point out the validity of independent component analysis based techniques as an adequate tool in order to evaluate saccadic waveform changes in patients of ataxia SCA-2.

1 Introduction

The ocular movement records have been widely used in processing and classification of biological signals and pathological conditions: clinical sleep scoring [10, 11], cerebellar dysfunctions [12-14], diagnosis of the visual system [15, 16], amongst others, also in human computer interface and visual guided devices [17-19]. The Spino Cerebellar Ataxia type 2 (SCA-2) is an autosomal dominant cerebellar hereditary ataxia with the highest prevalence in Cuba, reporting up to 43 cases per 100,000 inhabitants in the province of Holguin. In most families there is clinical and neuropathological evidence of additional involvement of brainstem, basal ganglia, spinal cord, and the peripheral nervous system [1]. This form of ataxia occurs commonly in persons of Spanish ancestry in north-eastern Cuba, a figure much higher than that found in western Cuba or in other parts of the world. The high prevalence is

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probably the result of a founder effect, but might be due to an interaction between a mutant gene and an unidentified environmental neurotoxin [2, 4].

Several studies have reported oculomotor abnormalities in SCA2 [1, 4-8]. Specifically, slowness of saccades has been suggested as a relatively characteristic finding in SCA2[4, 8]. This fact determines significant differences in saccade morphology between healthy individuals and patients with SCA-2, mainly for 60º of stimulus amplitude. The electro-oculographical records are quite different in healthy individuals and patients with a severe ataxia as it is shown in Figure 1 for a smooth pursuit experiment.

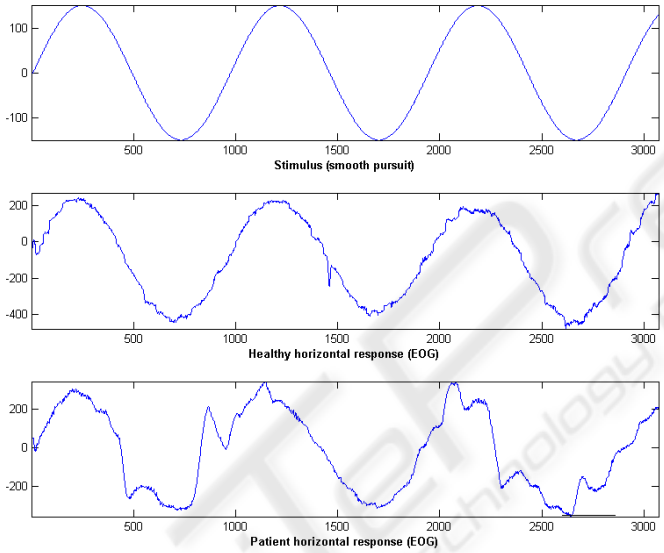

Fig. 1. Electro-oculographic response to a smooth pursuit stimulus (top) obtained for a healthy subject (center) and a patient of SCA-2 ataxia (bottom).

2 Using Blind Source Separation for Ataxia SCA2 Diagnosis

2.1 Hypothesis for the Proposed Method

Independent component analysis is aimed to find a linear transformation given by a matrix **W**, so that the random variables $\mathbf{y}_i$, (i=1,…,n) of $\mathbf{y}=[\mathbf{y}_1,\ldots,\mathbf{y}_n]$ are as independent as possible in:

$$\mathbf{y}(t) = \mathbf{W} \cdot \mathbf{x}(t) \tag{1}$$

This linear blind source separation approach is suitable for the signals obtained by the EOG, as well as in other medical analysis such as electroencephalography (EEG), electrocardiography (ECG), magneto-encephalography (MEG), and functional magnetic resonance imaging (fMRI) [20-26].

As it was shown in Section 1, in the analysis of EOG oriented to the detection of SCA2 experts anticipate two possible behaviors of the individuals: sick and healthy conduct. During an experiment over a healthy subject, the horizontal movement of the eye is expected to follow the stimulus signal. Therefore, the horizontal eye movement and the stimulus will hold a direct dependence between them, i.e. the signals are not independent. In contrast, a sick individual may present a more chaotic response, depending on the severity of the disease. Consequently, the subject response will not depend in such a high degree on the stimulus signal, and the signals are independent (or at least, "not so dependent").

Therefore, the proposed methodology uses independent component analysis as a classification algorithm criterion: if the independence measure (normally mutual information) reveals independence between the individual response and the stimulus signal, then it is rather possible that the individual presents some degree of ataxia or related disease.

2.2 Description of the Blind Source Separation Algorithm

The proposed algorithm for ataxia SCA-2 diagnosis will go along the following steps:

1. Set both horizontal response and stimulus signal in the same phase, i.e. correct the delay between the stimulus change and the saccade.
2. Normalize signals (x).
3. Apply ICA algorithm. Any well known ICA algorithm may be applied at this point (FastICA [27], Jade [28], GaBSS [29-30], etc.).
4. Normalize estimations (y)
5. Calculate error measure between estimations (y) and mixtures (x) according to the root mean square error expression:

$$RMSE(\mathbf{x}_i, \mathbf{y}_i) = \sqrt{\frac{\sum_{t=0}^{N} \left[x(t) - y(t)\right]^2}{N}} \tag{2}$$

6. Depending on the obtained error measure, a simple categorization algorithm (such as C-means) may be applied in order to classify individuals. Otherwise, a human expert may help in subject categorization based on the ICA results.

3 Results

The electro-oculogram recordings of six patients with severe ataxia and six healthy subjects diagnosed and classified in the "Centre for the Research and Rehabilitation of Hereditary Ataxias (CIRAH)" were used in order to perform the analysis of repeated ocular saccadic movement tests for 10º, 20º, 30º and 60º divergence stimuli.

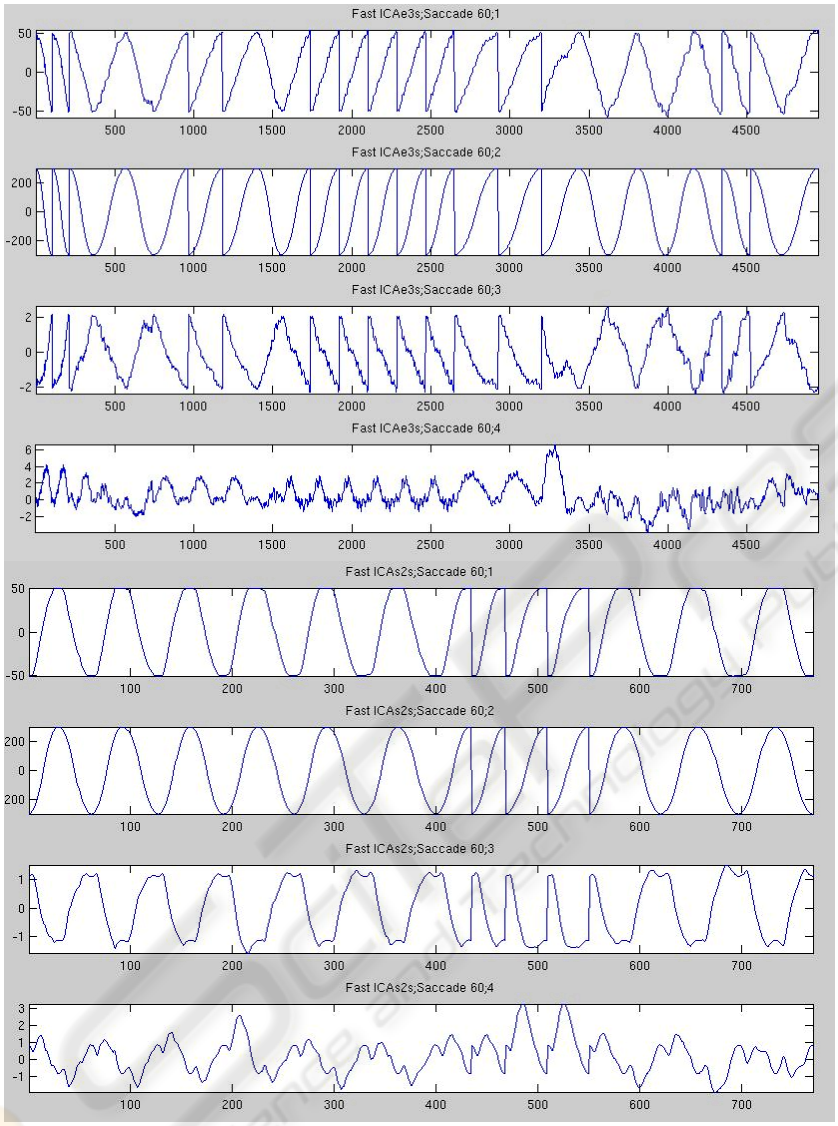

Fig. 2. Stimulus (1), response (2) and ICA components (3 and 4) obtained at 60º of stimulation for patients (top) and control subjects (bottom).

All the records were carried out by the medical staff of CIRAH. Each individual was placed in a chair, with a head fixation device to avoid head movements, the variables were collected by a two channel electronystagmograph (Otoscreen, Jaeger-Toennies). Recording conditions were set as follows: electrodes of silver chloride placed in the external borders of right eye (active electrode) and left eye (reference electrode), high pass filtering 0.002 Hz, low pass filtering 20 Hz, sensitivity 200 μV/division, and sampling frequency 200 Hz. For stimulus generation a black screen CRT display showing a white circular target with an angular size of 0.7º was used.

The stimulus and patient response data are automatically stored in ASCII files by Otoscreen electronystagmograph.

The patient response was filtered using a median filter, to obtain a clean waveform of the patient response, afterwards it was phased with the stimulus. Finally FastICA was applied to get the independent components (See Figure 2).

As Figure 3 depicts, results show that the error measure obtained for SCA-2 patients is clearly differentiable for the same measure obtained for control subjects. That is due to the fact mentioned in the hypothesis (Section 2.1) that if the independence measure reveals independence between the individual response and the stimulus signal, then it is possible that the individual presents some degree of ataxia. When the original signals (stimulus and response) were independent, the estimations are close to those sources and, therefore, the RMS error decreases.

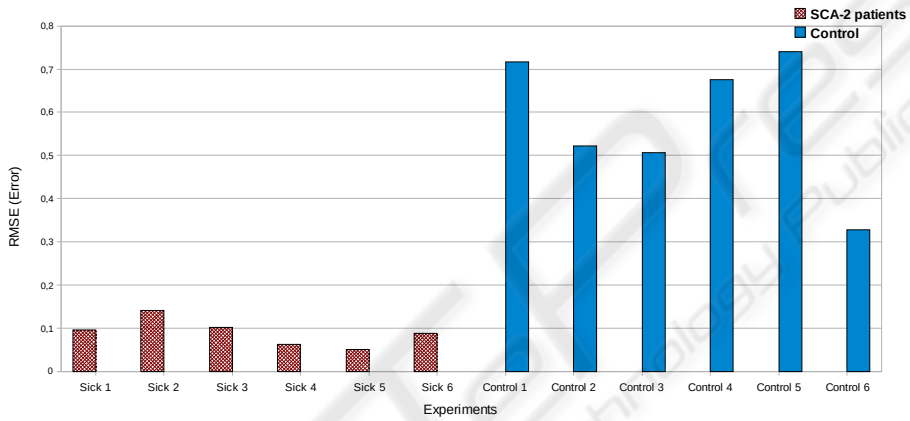

Fig. 3. Root mean squared error between the estimations and the sources after the application of the algorithm to EOG data corresponding to SCA-2 patients (left) and control subjects (right).

4 Discussion

The results were obtained from six control subjects and six patients. Confirming our hypothesis, starting from electro-oculography experiments, patients showed a different behavior in terms of the visual response to a fixed stimulus (see Figure 2 and Figure 3). Therefore, after applying our proposed approach to the raw EOG data, classification and diagnosis can be made easily by simple human inspection of the results. Nevertheless, further research in this line may help in the categorization of the several stages of severity of SCA-2.

The proposed method starts from the assumption that the response to a visual stimulus is different in a healthy individual when compared to the response of an individual afflicted by SCA-2. In the later situation, the response from the individual is not dependent on the visual stimulus, so that the ICA algorithm estimations will be similar to the obtained observations. This criterion has shown to be suitable in order to distinguish between sick (patients) and healthy (control) individuals.

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