Saccadic Points Classification Using Multilayer Perceptron and Random Forest Classifiers in EOG Recordings of Patients with Ataxia SCA2

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Abstract. In this paper, we compare the performance of two different methods for the task of electrooculogram saccadic points classification in patients with Ataxia SCA2: *Multilayer Perceptrons* (MLP) and *Random Forest*. First we segment the recordings of 6 subjects into ranges of saccadic and non-saccadic points as the basis of supervised learning. Then, we randomly select a set of cases based on the velocity profile near each selected point for training and validation purposes using percent split scheme. Obtained results show that both methods have similar performance in classification matter, and seems to be suitable to solve the problem of saccadic point classification in electrooculographic records from subjects with Ataxia SCA2.

Keywords: eog signals, multilayer perceptron, random forest, saccades, ataxia sca2.

1 Introduction

Electrooculography is a common technique for measuring eye movements due its affordability and its accuracy. In the Centre for Research and Rehabilitation of Hereditary Ataxias (CIRAH) of Cuba, this technique is used for monitoring of patients with hereditary ataxias. Specifically, saccadic eye movements have an special interest for the researchers of this disease. This is because many parameters calculated from eye movements are affected by the evolution of this disease [1].

Saccades are a kind of eye movements, according [2] are rapid jerk-like movements of the eyes that direct the gaze to a new location, and ballistic movements in the sense of their duration. Saccadic points are those where the saccade begins and ends, but there is no unified criterium about where exactly begins or ends

a saccade. Currently the identification of these points is performed by manual means by experts in the area or automatically by computational algorithms.

Identification by manual means have drawbacks such as the subjectivity introduced by the expert which makes the points selection. This subjectivity generates variability between the identification performed by various of these experts. In the case of signals recorded to sick subjects, the difficulties of manual identification rises due the presence of noises and conditions inherent of the disease.

The way of detecting saccadic points by computational methods is very varied and somehow formalized by the taxonomy of Salvucci-Goldberg [3]. Among the methods described by the taxonomy the most common ones are those based on velocity thresholds. These methods have as main drawback that for subjects affected severely by neurological diseases such as Ataxia SCA2, the identification of saccadic points is very inaccurate. Besides there is no consensus in the literature about what value should take the velocity threshold used by these methods. There is a serious lack of research about the other methods proposed in the taxonomy, but presumably there is a notable difference in the results yielded by them and those yielded by velocity thresholds based methods.

From saccadic points and the corresponding signal channel, is possible to calculate saccadic features such as maximum velocity, latency, duration and the amplitude. These features have proven to be useful in the research of many neurological diseases due the contrast of the behaviour of these features between patients and healtly individuals, as well as between patients of different diseases. For instance, saccadic velocity is significantly slower in subjects with SCA2 than in control subjects or subjects with other ataxias like SCA1 or SCA3 [4]. Also, the calculation of these features supports drug clinical trials and other kind of efforts to improve living conditions of subjects suffering this disease [1].

Latency, duration and amplitude are features very susceptible to the position of the saccadic points. So, the variability obtained by the methods currently employed have a negative impact on the utility of final data. On the other hand, the variability caused by the currently employed methods has a negative consequence on the interpretation of these features by experts, leading to misdiagnosis.

Form this considerations, new methods have to be explored to solve the problem of identification of saccadic points. Here we propose two methods based on computational intelligence, capable of learning from a set of examples. Machine Learning, specifically the supervised learning is a branch of Artificial Intelligence often used to solve classification problems. Also these techniques are used in the task of classifying EOG signal patterns [5,6,7]. In this paper we apply two different techniques of supervised learning to attack the problem of the saccadic and non-saccadic point classification in subjects with Ataxia SCA2, and analize their performance. We aim to obtain results with high accuracy without the drawbacks present in traditional identification mechanisms.

The rest of this paper is organized as follows: In section 2 we describe the designed experiments and available data. Section 3 is devoted to analize and comment the results. Finally, section 4 summarizes the main conclusions and future work lines.

2   Material and Methods

An experiment was designed to apply two machine learning techniques: Multilayer Perceptron (MLP) and Random Forest, to clasify a velocity saccadic pattern dataset. The experiment was separated in several stages as shown in Figure 1. The work performed in each stage is described more deeply in the followings sections.
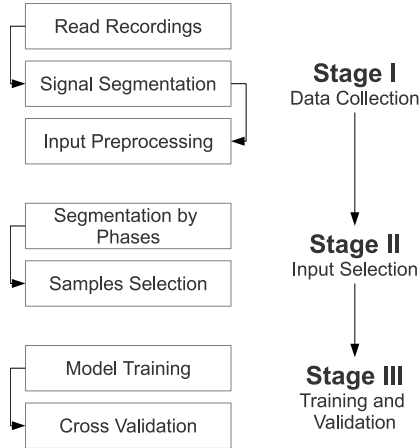

Fig. 1. Experiment main flow. Each stage are separated in a sequence of ordered steps.

In summary, each stage describes:

Stage I: Provide a set of cases that will conform the population used by the next stage. This population is builded based of EOG segmented data (saccadic or non-saccadic) created in this stage.

Stage II: Selection of training and validation data taking into account to balance the most typical cases.

Stage III: Training and validation of both classifiers, using percentage split scheme to separate training data and validation data.

2.1   Data Collection

The data was recorded using the Otoscreen electronystamograph at a sampling rate of 204.8 Hz with a bandwith of 0.02 to 70 Hz (analogic filtering). Specifically, 60 degrees saccadic signals were selected due to it's difference between healthy and sick subjects. Researchers from the *Centre of Research and Rehabilitation of Hereditary Ataxias* (CIRAH in spanish) provide us about 30 records of sick subjects, many of them in very bad shape. After the analysis of these records, only six of them meets good quality requirements to train classifiers.
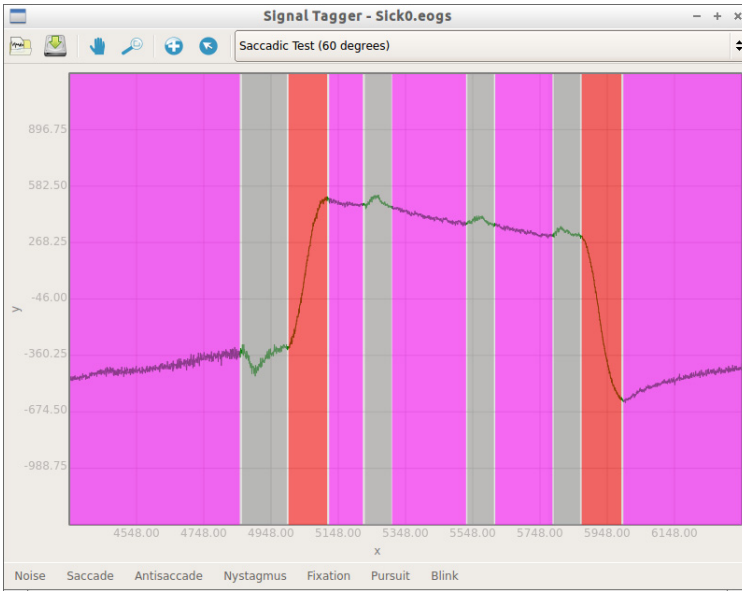
Fig. 2. Signal editor main window. Pink segments mean *fixations*, gray segments mean *noise* and red segments mean *saccades*.

For signal segmentation purposes, a desktop application was developed capable to mark different types of segments as shown in Figure 2.

All the programming was done in Python language using NumPy and SciPy open source libraries for numerical calulations, and PySide Qt bindings for graphical user interface. The application uses **python-eog** for reading and writing the data managed by the user interface, developed by the authors too.

Even when the application is capable to tag many ocular events, in selected test only saccades, fixations and noise are relevant. For practical reasons we only need to discriminate saccades and non-saccades, thus, our task becomes a binary classification problem.

Many classical algorithms used to detect saccadic eye movements use a velocity threshold to set the initial and ending points of a single saccade. Even when they not agreed in a threshold value, there is a consensus about that the main criterion is the velocity. Thus, it seems reasonable to think that the pattern of velocities preceding and after a certain point in the signal determines if they are inside or outside of a certain event as shown in Figure 3.

The idea for input variables of a single case, was get the pattern of velocities before and after the target point, in a window fashion way. To build the cases population, an sliding window runs through each tagged point in selected records, using this tag as the classification class. If this tag is a saccade we mark the sample as a saccadic point, if the tag is fixation or noise we mark the sample as non-saccadic point.
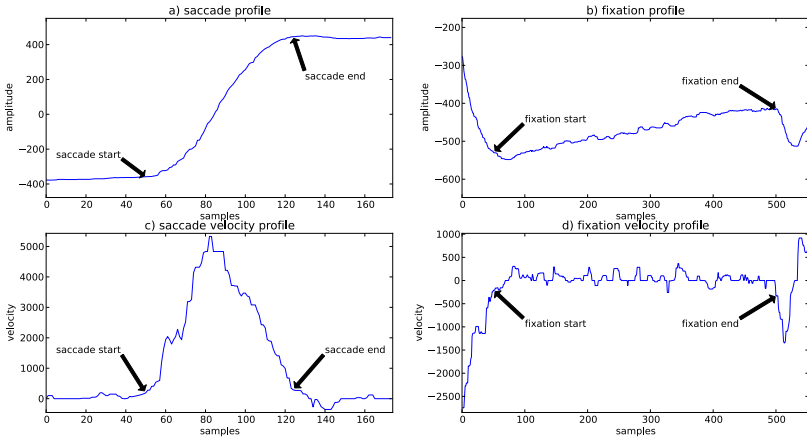
Fig. 3. a) Time signal of a sample saccade, **b)** Time signal of a sample fixation, **c)** Velocity profile of a), **d)** Velocity profile of b)

Filtering is, very often, the preprocessing part of signal analysis. For velocity profile calculations the input signal is first filtered using a median filter with a window size of 53.71 ms. After filtering, the velocity profile is calculated using a central difference by eight points method, which has proven to be adequate to signal sampled by 200 Hz [8]. Finally, new filtering is carried out to eliminate differentiation noise.

This aggresive filtering is posible because we are interested only in the relationship between the samples in velocity profile, not the waveform itself.

2.2   Input Selection

Once gathered instances population, we proceed to select the samples used for training and validation purposes. Is very important to provide a balanced set of input cases to the classifier in order to achieve better classification performance.

First, the number of cases used for training and validation process selected was 5000. The first half of them was devoted to saccade points and the another half to non saccadic points. The set of non-saccadic points was divided in fixation and noise ponits in equal proportions.

In Figure 4 is showed how different points belonging to the same saccade have a significative different window of velocities. That's mean that a point at beginning of the saccade usually have different window pattern than a point at the end of the saccade.

To get even more balanced set of data, was selected the same proportion of beginning, middle and end points of each class. As results of this input selection strategy, the samples count per class lays out in Table 1.
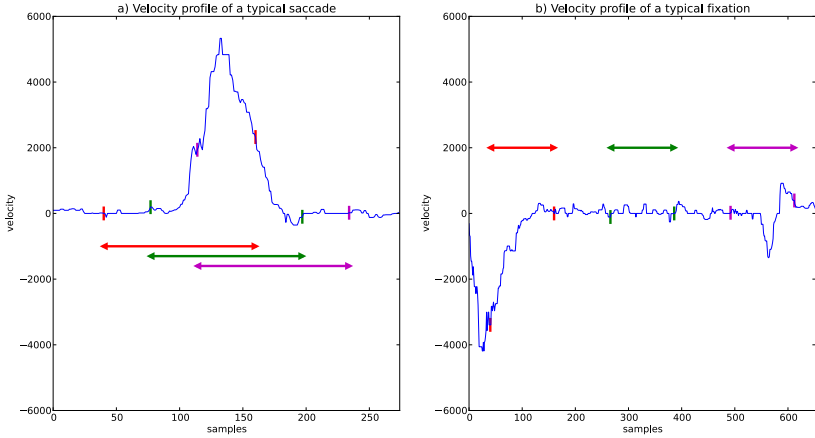
Fig. 4. Example of windows of points at beginning, middle and ending of an event. *Red* range means a window of a point at beginning of the saccade in a) and fixation in b). *Green* range means a window of a point at middle of the saccade in a) and fixation in b). *Magenta* range means a window of a point at ending of the saccade in a) and fixation in b).

Table 1. Distribution of input samples per zone in the event and per event itself

	Saccade	Non-Saccade Fixation	Noise	Total
Start	833	417	417	1667
Middle	834	416	416	1666
End	833	417	417	1667
Total	2500	1250	1250	*5000*

2.3   Training and Validation

Weka [9] is the software package used for training and validate the selected data.

Previous experiments carried out by the authors indicate that the optimum input features count for the MLP and RF input is of 121 components.

Multilayer Perceptron. MLPs are a kind of feedforward artificial neural network which consists in multiples layers of nodes in a directed graph, where each layer is fully connected to the next. Except for the input nodes, each node is a processing element with a nonlinear activation function.

The MLP classifier was trained with a topology of 121 nodes in input layer, 61 sigmoid nodes in the hidden layer and 1 linear node in the output layer. The network use backpropagation as training algorithm with a learning rate of 0.3 and a momentum of 0.2. 500 epochs were used to train this model.

Random Forests. RF is a ensemble of decision trees proposed by Leo Breiman [10]. The idea is based on building a forest of N decision trees, where in each trees we select M input cases in a random way using the same statistical distribution. Breiman in his paper proposes the use of Random Trees in the ensemble. In this type of trees, the split of features in each node is selected randomly from the K best splits.

Weka uses the algorithm proposed by Breiman. In our case we used the default values used in the package. This mean that our model will generate an ensemble of 10 Random Tree. For each tree the random split has 8 features.

The classification is made by the vote of each tree in the ensemble and selecting the most popular class among them.

The speed and accuracy of RFs make them a very good choice for problems related to computer vision. So we expect very good results from them, because the problem we are treating is in some extent a computer vision problem.

The training process uses 5000 examples distributed as shown in Table 1. The training were evaluated using cross-validation with 5 folds. Finally we test the trained model against 5000 new examples not present in training data.

3   Results

The validation process performed by weka states the following results:

In Table 2 *Training Cross-validation* stands for the results obtained in the training process, and *Real Validation* stands for the results obtained in the test process (patterns not presented in the training process).

Is a common practice in comparison of several classifiers to use metrics like sensitivity, specificity and accuracy. These metrics are derived from results shown in Table 2 and describe proportions between right and wrong predicted cases.

Sensitivity yields how good the model can predict possitive examples described by equation 1, in this case saccade points.

$$Sensitivity = \frac{TP}{FN + TP} * 100 \qquad (1)$$

Specificity is the proportion on correct prediction on negative cases described by equation 2, in this case non-saccade points.

$$Specificity = \frac{TN}{TN + FP} * 100 \qquad (2)$$

Table 2. Validation results for both classifiers, in training and validation data. **TP** are True Positive cases, **FP** are False Positive cases, **TN** are True Negative cases and **FN** are False Negative cases.

Classifier	TP	FP	TN	FN
MLP Training Cross-validation	2325	175	2323	177
MLP Real Validation	2291	209	2318	182
RF Training Cross-validation	2375	125	2334	166
RF Real Validation	2387	113	2318	182

Accuracy is the proportion of right predicted cases, described by equation 3.

$$Accuracy = \frac{TN + TP}{TN + FP + FN + TP} * 100 \tag{3}$$

Table 3 shows that both methods perform very well and very similar for the proposed task. However, these results also shows that the Random Forest performs slightly better than the Multilayer Perceptron.

Table 3. Performance metrics comparison between Multilayer Perceptron and Random Forest classifiers in training and validation data

Classifier	Sensitivity	Specificity	Accuracy
MLP Training Cross-validation	92.93 %	92.99 %	92.96 %
MLP Real Validation	92.64 %	91.73 %	92.18 %
RF Training Cross-validation	93.47 %	94.92 %	94.18 %
RF Real Validation	92.92 %	95.35 %	94.10 %

4   Conclusions

This paper presented a comparative between two machine learning techniques (Multilayer Perceptron and Random Forest) to solve saccade and non-saccade point classification problem of EOG signals measured tosubjects with Ataxia SCA2.

The results obtained by the validation of both methods shown an accuracy above 92 percent. So, they are suitable to solve the proposed task without the drawbacks present in traditional methods. Also, this results stated a slightly better performance for Random Forest than Multilayer Perceptron.

The Random Forest classifier could be used to build a pseudo-realtime identification system due its performance in relation to training speed, and for its accuracy.

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