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Comparison of LSTM and Patternnet for Classification of Eye Movements in EOG Signals

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ABSTRACT

In the fields of artificial intelligence and biomedical engineering, human-computer interaction (HCI) has evolved into an emerging technology. The basis of HCI technology is to obtain several important signals such as EOG, EMG and EEG to control an external device or computer. Using EOG data, this study seeks to determine eye movement for communication by persons with disabilities. Eog capture causes left and right eye movements to be detected. Then the right or left eye movement is evaluated. The type of movement (left, right) is classified using artificial intelligence algorithms. In this paper, we used classification algorithms (LSTM and PATTERNNET) along with a set of statistical features to classify eye movement direction. This study attempts to help people with disabilities control outdoor equipment such as wheelchairs, computer mice, robotic arms, and smart homes.

Keywords: Eye Movement , Lstm , PatternNet, Human-Computer Interaction ,Eog.

I. INTRODUCTION

Human Computer Interface (HCI) technology has worked with many bio signals in recent years. EOG, EMG, EEG, fNIRS, and other bio-potentials can be used in HCI applications [1-2]. Neuro-motor difficulties can result from diseases such as amyotropic lateral sclerosis, spinal cord damage, and others, making it difficult to control limb movements. By providing motor, sensory, or cognitive modalities, human computer interfacing (HCI) technology can help recreate the activities of a lost or damaged bodily part [1]. Various modalities of bio-signals can be used to develop Human Computer Interfaced rehabilitative aids, with Electrooculography (EOG) being one of the most effective. It is non-invasive, low-cost, simple to get, and may be processed in real time. Up to a point, eye movement has been shown to have a linear relationship with EOG amplitude.

EOG-based device control can be utilized to control neuroprosthetic devices [2], computer cursor motion [3], and wheelchair systems for rehabilitation [4]. Different methodologies for assessing [5] and implementing EOG [6] for control application [7, 8, 9] have been proposed. The EOG has proven to be the most straightforward method for determining eye movement directions. EOG systems with surface electrodes around the orifice are simple to build and alter in real time. The EOG technique allows us to forecast the existence of the disease in a straightforward and cost-effective manner, given the symptoms are highly characterized by eye movements [10].

The EOG is a good alternative to hand gestures and speech for HCI. EOG signals are commonly employed in HMI applications such as computer control and wheelchairs, as these programs allow individuals with impairments to navigate and operate their computer applications [11]. As a result, the EOG is a good candidate for being used as an eye movement input. Indeed, EOG has been presented as an input for a range of HCI indicators, including control of an electric wheelchair [12], control of a mobile robot [13], recognition activity [14], and recognition of eye writing [14,15].

The authors of [16] proposed DOSbFC, a new electrode placement approach based on eye glasses, as well as a base line drift and noise removal method. The average accuracy of BPF and wavelet transformation was 61 percent and 64 percent, respectively, whereas DOSbFC long-term eye movement detection was 94 percent, according to the findings. The authors of [17] concentrated on determining the spatial position of the eye, recognizing different eye movements using EOG signals, and inventing new coding approaches that users might employ to connect with EOG-based virtual keyboards. This trend enables asynchronous and direct access to any image from any location on the screen. The saccade and blink labeling accuracy in this system was 99.92 percent and 100.00 per cent respectively.

The EOG system was created in [20] to detect eye movements that can help people with defective face muscles and limbs regain communication skills. The DT, KNN, EC, KNB, and SVM classification models were employed for feature extraction and classification of horizontal and vertical channel data. This system has a 78 percent accuracy rating. The main goal of this research is to test and compare the classification accuracy and training duration of several classifiers (lstm, patternnet) for horizontal eye motions (right and left). On EOG signals, this research also looks at a statistical feature extraction method.

II. MATERIALS AND METHODS

2.1. Data set

The usefulness of EOG signals in categorizing horizontal eye movements is being investigated using a publicly available data collection. The EOG Database was employed in this study as a data source. Electrocardiogram (EOG) data from six healthy people (2 males and 4 females; mean age 24.7±3.1 years) is included in this data collection.

On a separate cue on the screen, subjects were asked to identify their point of view (POG). A total of four trials were recorded, as shown in Figure 1, in which the subject was requested to complete a goal that started from the center of the screen and ended at a random target location in the first 1 second. After that, there was a return movement. in the following seconds, matching to the middle of the screen, flashing in the last two seconds of each trial For each subject, a total of 300 trials were recorded in three separate sessions, with 100 trials being recorded in each session. Between sessions, there were intermittent pauses. The EOG signals were acquired with a sampling frequency of Fs = 256 Hz using the g.tec g.USBamp bio-signal amplifier (g.tec medical engineering GmbH, Austria) [23].

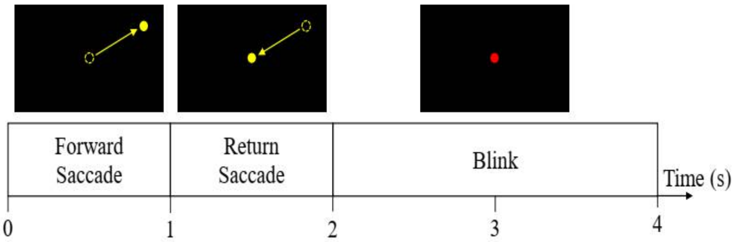

Figure1: EOG capture session

2.2. Data Preprocessing
Noises and other interferences, such as eye blinks, powerline interference, head movements, and so on, regularly corrupt EOG signals. A bandpass filter with a frequency range of 0-30 Hz and a notch filter with a frequency range of 50 Hz were used to filter the collected data.

2.3. Feature Extraction
Because of signal noise caused by eye blinks, EMG from facial responses, improper electrode placement, brightness effects, and other factors, classification using raw EOG signals would be time consuming and unsuccessful. Another significant disadvantage would be the huge processing cost incurred as a result of the massive amount of the input data. However, certain properties can be used to represent EOG signals. These characteristics can be used to characterize signals as features.
Feature extraction is a technique for obtaining these features. Feature extraction is critical for extracting a unique pattern from a collection without losing important information. In other words, feature extraction reduces data dimensionality while simultaneously increasing inter-class separability and intra-class similarity. Statistical characteristics [24] are used in this study. To characterize EOG signals, the following 10 statistical properties of EOG single channel (horizontal eye movement) are employed as parameters:

I. Minimum
II. Maximum
III. Mean
IV. Median
V. Mode
VI. First quartile
VII. Third quartile
VIII. Interquartile range
IX. Standard deviation
X. Kurtosis coefficients

2.4. Classification
Classification is performed on the feature set obtained from the raw EOG signal as described above using two different classification techniques: an LSTM classifier and a PATTERNNET classifier.

2.4.1. LSTM classifier
Long short-term memory (LSTM) is a deep learning architecture that uses an artificial repeating neural network (RNN). LSTM has feedback links, unlike normal feed forward neural networks. It can process whole data series as well as single data points (such as photos) (such as speech or video).

The classification of right and left eye movement is done in this work using a five-layer LSTM architecture. The temporal and extremely non-linear structure of the EOG signal inspired the use of RNNs to classify it [25]. We employed RNN with LSTM modules in this research. The network used the statistical data acquired in the previous stage to produce a two-category classification (right, left). The structure of the proposed RNN in this study was as follows:

A sequential layer with 30 time steps was utilized as the input layer, while LSTM layers were employed to learn features from EOG signals. The fully connected layer (FC) was utilized to translate the output volume of the previous layers into the number of sleep phases needed to identify them. The classification output layer produced the cost function after the softmax layer estimated the probability of each target class across all potential target groups. The output potential range is the key benefit of utilizing the softmax activation function. The output values of this function range from 0 to 1, and the total number of possibilities is one. The following is her mathematical expression:

$$\hat{y}_j^{(i)} = \frac{e^{z_j^{(i)}}}{\sum_{j=1}^{C} e^{z_j^{(i)}}} \tag{1}$$

The superscript I stands for the general training example, j for the FC layer's general neuron, z for the FC layer's output value, and C for the number of target classes. The cost function is a function of all weights and bias conditions, and it is minimized during the network training process.

2.4.2. PatternNet classifier

Feedforward networks that can be trained to classify inputs into target classes are known as pattern recognition networks. Pattern recognition networks' target data should be vectors with all zero values except a 1 in element I where I is the class they're supposed to represent[26].

PatternNet provides a pattern recognition neural network with hidden layer sizes of hidden Sizes, a training function, train Fcn, and a performance function, perform Fcn, as well as a training function, train Fcn.
Structure of a Classifier With the previously extracted feature set as the input data, create a pattern network with three hidden layers of size (10,8,5) to categorize two eye movements (right and left) as shown in Figure 2.

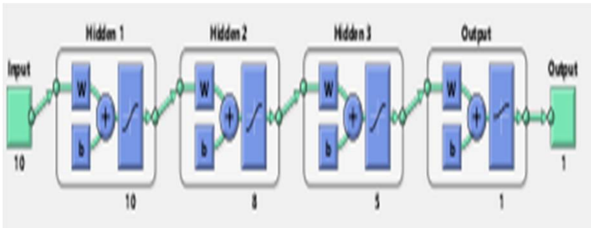

Figure 2: Structure of Pattern Net algorithm.

III. RESULTS AND DISCUSSIONS

(a) Denoise removal for signals

A 0-30 Hz bandpass filter and a 50 Hz notch filter are used to filter the collected data to remove noise and other interference, such as eye flicker, power line interference, head movements, etc. that corrupt the regularity of EOG signals, as shown in Figure 3.

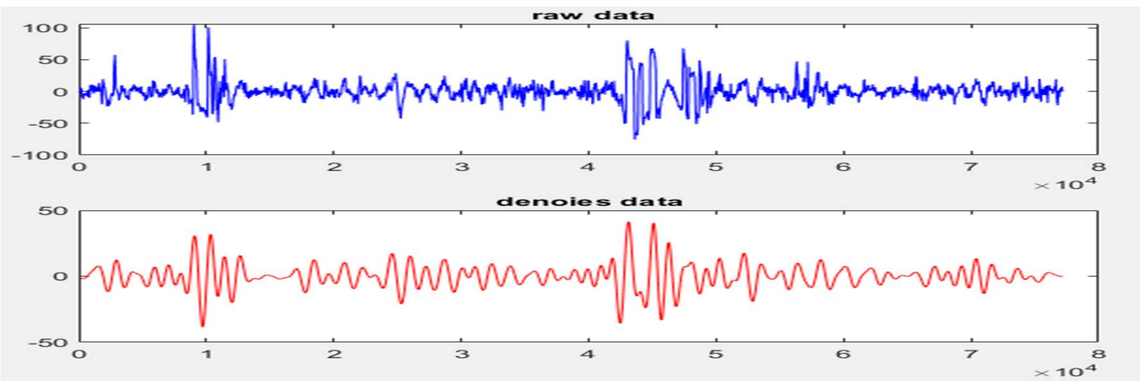

Figure 3: EOG signals before and after preprocessing .

(b) **Building feature sets**

In each subject's three EOG reading sessions, 30% of the EOG signals are recognized as test data. The remaining 70% is used for training purposes. From this data, ten statistical features are retrieved. Training vectors are used to train classifiers (LSTM, PATTERNET), while test vectors are used to evaluate the accuracy and effectiveness of the learned models.

(c) **PatternNet And LSTM Comparison**

The performance of classifiers is examined per subject in this research. The usage of test accuracy and training time is used to evaluate and compare performance. The fraction of actual positives that are expected to be positive is used to assess classification accuracy .

Classification accuracy(%) = $[\frac{NT}{(NT+NF)}] \times 100$

where NT is the number of trials in which the forecast was correct and NF denotes the number of trials in which the prediction was incorrect. Under the same feature data as input, both classifiers performed well based on the results from Tables 1 and 2. It provides results that are very comparable . PatternNet is slightly better than LSTM in terms of rating rate when using statistical features, as well as taking a shorter training time.

When comparing the classification accuracy of the two algorithms, the feature extraction statistical method achieves the best accuracy when using a PatternNet classifier with an accuracy rate of 95% and a low training time of 0.965 sec. It can be seen from Table 1 that the LSTM with the statistical parameters as input also achieves a high accuracy estimated at 94.6% and is close to the classification accuracy at the PatternNet classifier and a training time of 3 seconds. In terms of training time for both classifiers, PatternNet outperforms LSTM in multiclass classification. This can be explained by how the classification model is trained under PatternNet. As a powerful supervised learning algorithm.

Table 1. Classification results for statistical parameters as features using LSTM as classifier.

Subjects	S1	S2	S3	S4	S5	S6	Overall classification accuracy (%
Classification accuracy (%)	96	96	93	94	91	98	94.6
Duration for training (s)	3	3	4	4	2	2	3

Table 2. Classification results for statistical parameters as features using PatternNet as classifier.

Subjects	S1	S2	S3	S4	S5	S6	Overall classification accuracy (%
Classification accuracy (%)	99	96	94	90	94	97	95
Duration for training (s)	0.96	0.97	0.96	0.98	0.96	0.96	0.965

IV. Conclusion

People with disabilities do not have the ability to communicate with their surroundings, so eye movements are used to create a means for them to communicate with their external surroundings. EOG signals were picked up to classify the different eye movements and gave high results.

An accuracy of 95% was obtained for the classification of horizontal eye movements using the PATTERNNET classifier, and an accuracy of 94.6 for the use of the LSTM classifier, after removing noise from the signals and extracting a set of statistical features to be used as input data for classification algorithms.

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