Wheelchair Controlling by eye movements using EOG based Human Machine Interface and Artificial Neural Network

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ABSTRACT
The use of vital signals as a connection interface between humans and computers has recently attracted a great deal of attention. The electro-oculogram (EOG) signal, which is due to eye potential, is one of these signals. More advanced, EOGbased Human-Machine Interfaces (HMIs) are widely investigated and considered to be a noble interface option for disabled people. Artificial neural networks were utilized in this study to detect eye movement from the EOG signal. Neural networks can detect and classify biological signals with nonlinear dynamics, including EOG signals, due to their ability to learn nonlinear dynamics and their pervasive approximation. In this study, two fundamentally distinct networks, MLP and ART, were used to detect sequential and random eye movements for controlling wheelchair. The results indicate that the MLP network could indeed detect consecutive eye movements with an accuracy of over 90%, although the accuracy of this network detection in the case of random movements is relatively poor. In the field of random eye movements, the greatest results are obtained using the ART2AE network, which allows having a diagnostic accuracy of over 70%.

General Terms
Artificial neural network, MLP network, ART2A-E network.

Keywords
EOG, Human-Machine Interfaces (HMIs), Eye movements Tracking, MLP, ART

1. INTRODUCTION
Nowadays, recognizing the quantity and direction of eyeball movement has become the subject of extensive research in the field of Human-Machine Interactions [1]. In the past few years, we also have seen an exponential evolution in the development of Human-Computer Interface (HCI) systems. These systems have been applied for a wide range of purposes like controlling a computer cursor [2], a virtual keyboard [3, a prosthesis [4], or a wheelchair [4–7]. They could also be used for patient rehabilitation [8]. HCI systems can make use of different input signals such as voice [5], Electromyography (EMG) [9], Electroencephalography (EEG) [10], Near-Infrared Spectroscopy (NIRS) [11] or Electrooculography (EOG) [2]. Various methods have been proposed for recording eye movements so far [1]. The use of electrooculogram (EOG) signal processing, which is also considered in this study, is one of the most appropriate and cost-effective diagnostic methods for eyeball movement detection. In 1920, the ability to record an electrical potential by inserting surface electrodes in the area around the eye was first discovered [2]. Initially, it was believed that the induced electrical activity caused by eye movements was dependent on the action potential of the eye muscles. It is now accepted that the induced electric potential depends on a permanent potential difference, which is located between the cornea and the retina and has an almost linear connection with eye movements, called Corneal-Retinal Potential (CRP) [2]. The act of recording this potential is called an electro-oculogram and the signal resulting from recording this potential is called an Electro-oculogram (EOG). As previously mentioned, electro-oculography is one of the most appropriate and cost-effective techniques of recording eye movements. For the first time in 1995, an EOG-based computer interface for human-computer Interaction was designed (Kaufman, 1995) [12]. In 1998, a four-dimensional ocular mouse was introduced to assist people suffering from brain and spinal cord diseases (Tomita, 1998) [12]. The Corneal-Retinal Potential (CRP) generates an electric field in the tissue surrounding the eye, and the eye rotation results in a corresponding rotation in the field vector. However, this is only an estimate of the actual biological system, as the tissue around the eye has an irregular form. It's worth noting that the link between eye movements and the EOG signal can only be presumed to be linear within a 30-degree range. The measurement of horizontal eye displacements obtained by placing a pair of electrodes on either side of the eye can be seen in Figure 1.

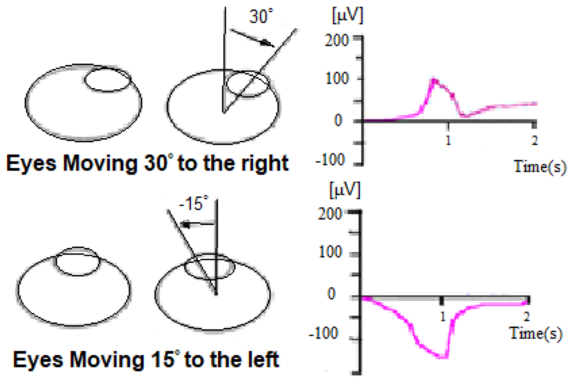

Fig 1: EOG signal generated by horizontal eye movement

As previously noted, one of the most widely used methods in the field of eye movement detection is EOG signal processing and classification. So, the need to use an appropriate classifier in this case is obvious. The ability to learn nonlinear dynamics and pervasive approximation are important features of neuralnetworks, and this makes them a suitable tool in detecting and classifying biological signals, including EOG signals. In a general category, these networks may be divided into two types: static and dynamic networks. Networks with memoryless nodes, including multilayer perceptron, are called static networks. The nodes of these networks have no linear dynamics. Dynamic neural networks are a type of neural network that is more significant than static neural networks. These networks are significant since most of the real systems we seek to model are nonlinear dynamic systems. Bulling et al. classified six eye-movement activities (copying, reading, writing, watching a video, browsing, and no activity) with the use of dry electrodes leading to an accuracy (F1 score) of 68.5 [13], and they also reported the classification of eight eye-gestures with an accuracy of 87% [14]. Ianez et al. recognized six-directional eye-movements with an accuracy of 90% [15] Even though electrooculogram (EOG)-based devices have not been extensively developed, in contrast to other modalities, they may provide possible solutions for the current limitations of visual-based BCI systems. In comparison with EEG, EOG can be acquired using a fewer number of electrodes. Unlike camera-based eye tracking devices, the EOG-based AAC devices do not need additional systems (e.g., infrared cameras) except for a signal amplifier. Despite these advantages of EOG-based AAC systems, however, the current EOG-based systems require the user's voluntary movement of eyeballs. It seems obvious that patients with oculomotor impairment would require more efforts to voluntarily control eyeballs compared to performing simple mental tasks, e.g., directing concentration towards a target sound source [16]. In this paper, a method of detecting the direction of eye movement from the EOG signal using artificial neural networks is prenboiv7jsented. Four different types of eye movements are considered in this study, which could be divided into two categories: consecutive and random movements. In this study, a multilayer perceptron neural network (MLP) was applied to classify the four mentioned types of motion. It is noteworthy that some innovative external dynamics have been used to improve the performance of this network in this study. The adaptive resonance theory (ART network) is utilized in the second part. Two different versions of the ART network called ART-2A and ART2A-E are used in this article. The results demonstrate that the MLP network performs better in detecting consecutive movements while the ART network performs better in detecting the direction of random eye movements. The purpose of this article is to reveal the direction of eye movements so that they may be used in human-machine interactions

2. MATERIALS AND METHOD

Two networks, MLP and ART, were used in this study to detect consecutive and random eye movements, and the performance of these two networks was compared in the end. Various experiments have been done in order to gather the data required for training and testing classifiers (neural networks):

2.1 Data Acquisition

Each experiment in this study lasted 21 seconds and was obtained using the Powerlab system in the specialized laboratory of Islamic Azad University, Mashhad Branch. The EOG signal was generated using five electrodes. Four electrodes were placed in the upper, lower, left, and right partsof the eye, and the fifth electrode was placed in the middle of the forehead as a reference. The following figure shows how to install these electrodes.

Fig 2: Installing electrodes for EOG signal acquisition

In this recording, subject sits simply in front of a computer, with no sound or light insulation, and follows a moving target that moves on the computer screen once every 2.5 seconds (or exactly every 2.54 seconds) with his eyes. At the same time, the introduced system amplifies the person's EOG signal, which is then sampled and transmitted to the computer at a rate of 256 Hz. Given that each experiment lasts approximately 35.5 seconds, and the moving target moves on the computer screen once every 2.5 seconds (or exactly every 2.54 seconds), subject performs 14 movements during the recording. The EOG signal for the first and last movements of these 14 movements is invalid and is discarded. Therefore, during each test, the testing eye makes 12 correct movements. The features of the EOG signal from the second to the twelfth motions (11 motions) are extracted and used in each test. Four types of moving targets are considered in this study including:

1 - Consecutive movements between two targets on the screen
2 - Consecutive movements between four targets on the screen
3 - Random movements between four targets on the screen
4 - Random movements between six targets on the screen

The following figure shows four types of moving targets

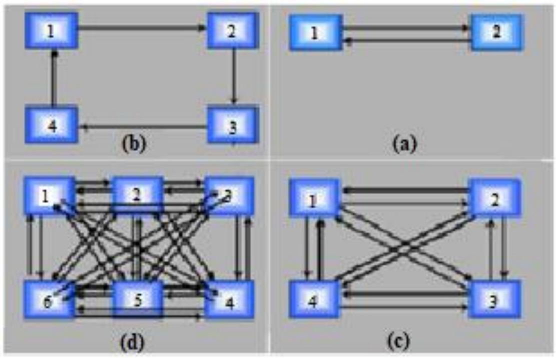

Figure 3- Eye movements patterns a) Consecutive movements between two goals b) Consecutive movements between four targets c) Random movement between four goals d) Random movement between six goals

In Type A goals, the left and right corners of thesecond type of moving target includes four movements right, down, left, andup and the purpose is to distinguish these four movements. Four and six goals are considered in type (c) and (d) goals, respectively, which are lit randomly, and the subject must follow these changes on the screen at all times. Considering that the total number of tests in each of the types of goals is 10 and the number of eye movements studied in each test is 11, so the total number of left and right eye movements that are used is 110 movements. 10 patterns are extracted from each test. Therefore, the total number of network input patterns will be 100 patterns, of which 60 patterns have been used to train the network and another 40 patterns have been used to evaluate the network performance in detecting eye movements.

2.2 Preprocessing

Figures 4 (a and b) show the recorded EOG signal due to sequential movements between the left and right corners of the screen and the signal resulting from successive movements between the four left, right, top and bottom corners. A low pass filter with a cut-off frequency of 30 Hz is used to process these signals in order to eliminate high frequency noise. After this stage, the DC surface is removed from the signal, as well as the artifact associated with involuntary eyelids. Removing the blinks from the EOG signal using the threshold method is done in such a way that on the vertical channel, the amplitude of the blinks is substantially larger than the amount of change in the amplitude of the EOG signal due to voluntary eye movements. Therefore, blinks may be identified and removed using a threshold value (removing it from the EOG signal). When moving left-right, a positive potential appears initially, following a negative potential in the horizontal channels. When moving left-right, however, a negative potential appears initially, following a positive potential. In horizontal motions, the number of potential changes in the horizontal channel is greater than the number of changes in the vertical channel. In vertical motion, the opposite occurs and the vertical channel will have strong peaks.

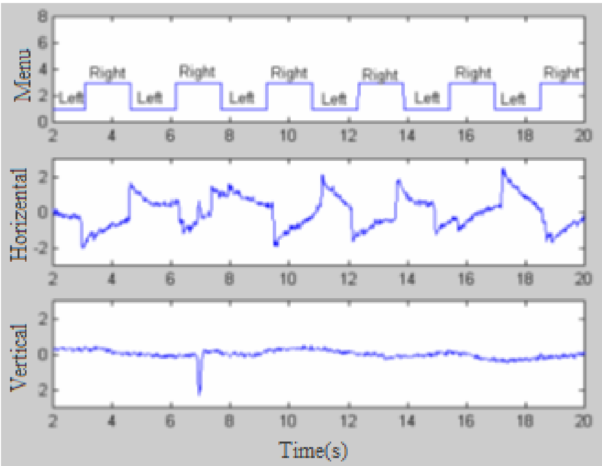

Fig 4- a- The signal caused by consecutive movements between two targets, after high frequency noise has been removed

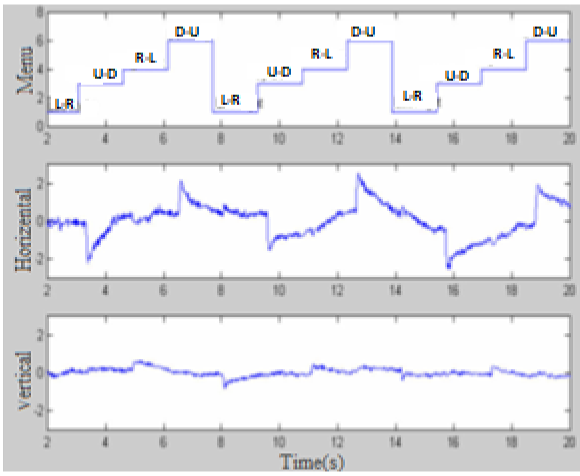

Fig 4- b- The signal caused by successive movements between four targets, after removing high frequency noise (Left, R=Right, U=Up, D=Down)

2.3 Feature extraction

In this study, the following patterns have been used to extract a feature from the signal:

1. Minimum

2. Maximum

3. Mean

4. Variance

5. Sharpness

6. Singular Values

In fact, these features constitute the classifier inputs (neural network).

Touse single-decomposition patterns, the signal is decomposed into a series of perpendicular vectors, of which the singular values are the special values of these vectors. Singular values remove information redundancies since the vectors are orthogonal, and therefore contain essential signal information. One of the best possible answers can be obtained using this template.

▪ Mean(x)=E[x]

▪ Variance(x)= E[(x-E(x)]

▪ Sharpness(x)= E([(x-E(x)]) ^ 3.

2.4 MLP network

Undoubtedly, Perceptronis one of the most practical and understandable types of neural networks. The general model of perceptron networks is a forward network with a backward diffusion training routine. Forward networks are networks in which the inputs of the first layer of neurons are connected to the next layers, and this is true at every level, until it reaches the output layer. The backward propagation process also implies that after determining the network's output, the weights of the last layer are rectified first, followed by the weights of the preceding layers in order. Perceptron networks consist of an input layer, several hidden layers, and an output layer. A perceptron neural network with two hidden layers can be seen in the following figure.

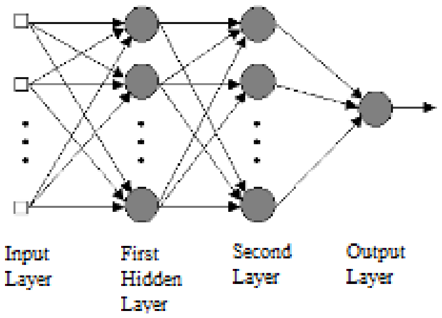

Fig5 - An example of a perceptron network with two hidden layers

In this study, a neural network with two hidden layers (15 neurons in the first hidden layer and 10 neurons in the second hidden layer) was employed after error propagation. The nonlinear function in hyperbolic form is also used in the hidden layers and the output layer. Network inputs are patterns extracted from the EOG signal due to eye movements. The learning rate is selected as 0.01. According to how many goals the user intends to achieve, the number of network outputs is 2, 4, or 6.

This innovation has been done on the MLP network for the first time in this study, in which the network outputs related to pre-eye movement are also given as input to the network. In other words, to train and evaluate the neural network to detect eye movements, the EOG signal properties related to the current and prior movement were applied as input to the network. The figure below depicts this idea, which was initially presented in this study.

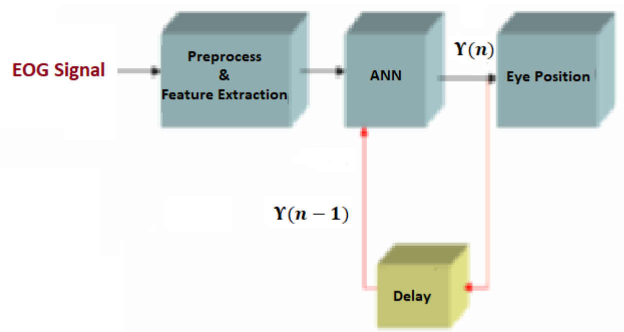

Fig6- Using current eye movements and pre-network output as neural network input

2.5 ART network

One of the autonomous structures, Adaptive Resonance Theory (ART), is capable of clustering a large number of input patterns into stable identification codes. Various ART networks have been developed to increase classification capabilities, including the FUZZY ART, ARTMAP, ART1, ART2A, and ART2 networks. The algorithm used in ART is closely related to the K-means algorithm and in both algorithms simple representatives are used as internal weights. The average of a data set is decomposed into category K. The parameter K specifies how the data is decomposed. The Kmeans algorithm divides a data set into K categories. The K parameter specifies how the data is divided. ART, on the other hand, categorizes objects based on pattern similarity. Therefore, the value of K (number of groups) in ART depends on the distance between the input patterns. ARTuses a quantitative parameter called the Vigilance parameter (p) to detect the degree of similarity of the data. In this study, two versions of the ART network called ART2A, and an improved version called E-ART2A have been used.

3. Results

As noted previously, the number of network input patterns for each type of target is 100. 60 of these features have been used for network training and another 40 for network testing. To achieve a more accurate result, the training templates have been selected in the form of the following 3 categories:

1- Patterns No. 1 to 50
2- 2 - Patterns No. 25 to 76
3- 3 - Patterns No. 51 to 100

3.1MLP network

As mentioned, the MLP network used in this study consists of two hidden layers. The number of input nodes in the network equals the sum of the number of input features and the number of targets (2, 4 and 6). The number of network input nodes is equal to the sum of the number of input features and the number of targets. For example, in the 4 corners of the image, the number of input neurons in the network is equal to 10 neurons (6 neurons are related to the input characteristics of the current motion and 4 neurons are related to the output of the 6-state mode network are equal to 12 neurons. The number of neurons in the secret layer has been addressed differently to investigate the effect of their number. The total results obtained in the detection of left-right movements (two objectives) are equal to 100% and the network with an interesting accuracy of 100% can classify between two movements to the right and left. In the section of detecting movements between 4 corners of the image in a row, the findings will be according to Table 1. The network can detect eye movements with a high accuracy of 97%, according to the findings. To analyze the impact of the number of hidden two-layer neurons on the total accuracy, their number is considered different, the results of which can be seen in Table2.

Table 1- Percentage detection of left, right, up, down (consecutive) movements by MLP network after 5000 learning sessions

	1st group	**2nd group**	**3rd group**	**Average**
Sharp single values	97.1	99.4	92.8	96.4
Average-Diffraction-Sharpness	100	100	92.8	97.6
Maximum-Minimum Average	100	100	92.5	97.5

Table 2- The effect of the number of hidden layer neurons on the correct diagnosis of consecutive four-way eye movements after 5000 learning periods

	Number of neurons intwo hidden layers		
	10-10	15-10	20-20
Sharp single values	98.6	97.6	97.1
Average- Diffraction-Sharpness	99.5	100	98.4
Maximum- Minimum Average	100	100	99.4

Those acquired for consecutive motions. Tables 3 and 4 demonstrate the results of four-objective and six-objective random movements, respectively.

Table 3- Percentage detection of 4-objective random movements by MLP network after 5000 learning courses

	1st group	2nd group	3rd group	Average
Sharp single values	64.7	64.3	55.3	62.0
Average-Diffraction-Sharpness	59.1	62.9	60.5	60.8
Maximum-Minimum Average	64.0	67.2	62.2	64.5

Table 4- Percentage detection of 6-objective random movements by MLP network after 5000 learning courses

	1st group	2nd group	3rd group	Average
Sharp single values	27.9	21.2	40.3	29.8
Average-Diffraction-Sharpness	38.9	35.6	28.7	34.4
Maximum-Minimum Average	34.4	36.6	32.5	35.4

3.2 ART network

Two types of ART network structures were utilized in this study as ART-2A and ART2A-E. The learning rate for both versions of ART used in this study is 0.1. For both networks, the similarity parameter (p) is set to be quite close to one (maximum value), requiring less repetition for network convergence. Training patterns are also applied tothe network randomly. Advantages of this training method is that the network tries to adapt to the constant changes of input, and in this respect the learning capacity of the network increases, but instead the learning speed decreases, and the training time increases. The number of network outputs is floating and using Array encryption method, the number of these outputs is reduced to the number of goals (or menus) desired by the user. The most significant reason for using ART network in this study is the inability of MLP network to detect random eye movements and as will be seen in the following tables, this network showed a better result than MLP network in detecting random eye movements.

Table 5- Percentage detection of 4-objective random movements by ART-2A network after 5 learning courses

	1st group	2nd group	3rd group	Average
Sharp single values	64.8	72.9	68.7	68.8
Average-Diffraction-Sharpness	60.4	62.1	57.6	60.0
Maximum-Minimum Average	31.9	36.4	64.4	44.2

Table 6- Percentage detection of 6-objective random movements by ART-2A network after 5 learning courses

	1st group	2nd group	3rd group	Average
Sharp single values	27.1	27.8	18.8	24.6
Average-Diffraction-Sharpness	37.9	40.0	35.7	37.9
Maximum-Minimum Average	36.4	34.4	32.1	34.3

Table 7- Percentage detection of 4-objective random movements by ART2A-E network after 10 learning courses

	1st group	2nd group	3rd group	Average
Sharp single values	83.9	78.8	81.1	81.3
Average-Diffraction-Sharpness	66.6	65.6	70.9	67.7

Maximum-Minimum Average	81.3	80.5	84.9	82.2

Table 8- Percentage detection of 6-objective random movements by ART2A-E network after 10 learning courses

	1st group	2nd group	3rd group	Average
Sharp single values	63.6	57.1	42.9	54.5
Average-Diffraction-Sharpness	50.4	57.9	45.6	51.3
Maximum-Minimum Average	70.2	73.0	81.9	75.0

4. CONCLUSION

A method to detect different eye movements from electrooculogram (EOG) signal using artificial neural networks is presented in this study. The detection of eye movements via EOG signal processing has advantages and disadvantages over other methods. The main disadvantage of this method is that the potential depends on the cornea and retina and is not constant and can change under the effect of light, fatigue and other personal characteristics [17]. Therefore, this method requires frequent re-calibration. Also, muscle artifacts have a negative effect on EOG recording. The benefit of this method is that recording EOG signals does not generally cause discomfort to the subject, and overall effective artifacts will be minor.

Researchers have previously utilized the EOG signal threshold to classify the signal and extract it for eye movement [2]. The flaw of this method includes the presence of drift in the signal and its changes in time and uncontrolled eyelids, which can reduce the accuracy of the diagnosis.

As observed in the results, the neural network-based approach mentioned in this study is capable of tracking eye movements with high accuracy. The efficiency of this method is higher than the threshold application method.

The MLP network with the structure given in this article can have accurate results in the detection section for consecutive eye movements (2 and 4 targets); however, this network does not have adequate accuracy in detecting the direction of random eye movements. Thus, networks based on ART theory have been used in this paper. Due to radial analysis of input pattern space, the A-ART network has poor results, while modified versions of this network, including the E-ART2A applied in this research, provide satisfactory outcomes.

Another drawback of employing the MLP network is that it has a relatively slow learning speed and a relatively long training time. It was discovered that the speed of convergence to the response is substantially higher than the network while using the ART network.

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