EOG based HCI to control GUI cursor

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***Abstract* – Our proposed project is a Human Computer interface headset to control computer cursor that uses EOG signals. This headset comes with a computer GUI which can help full body paralysis victims with functioning eye movements to control their environment to some extend and able to communicate using EOG based keyboard and speech synthesizer. The GUI will provide a human computer interface acting as a cursor control for the GUI. In this project, the EOG signal will be primarily used for cursor control of GUI. A level 6 Stationary Wavelet Transform (SWT) decomposition using Daubechies wavelet is used for signal de-noising. Time Domain analysis (Peak Amplitude Value, Valley Amplitude Value, Upper Wavelength and Lower Wavelength) and maximum global relative amplitude on orthogonally decomposed signals are used as feature extraction methods for the project. Support Vector Machine with Gaussian kernel and Neural Networks with cascaded feed forward network are used for classification of EOG signals. An accuracy of 90.79% and 96.93% were achieved with SVM and Neural Networks respectively.**

Index Terms – EOG, electrooculography, neural, paralysis, SVM, time-domain, wavelet.

I. INTRODUCTION

Paralysis is a loss of muscle function for one or more muscles. Paralysis can be accompanied by a loss of feeling (sensory loss) in the affected area if there is sensory damage as well as motor. For patients with partial or full body paralysis, doing day to day activities can be extremely challenging.

The main aim of this project is to develop a GUI which can be controlled using eye movement. This HCI based GUI will be designed keeping in mind the needs of victims of paralysis with control over their eyes. It will be used to control their environment like powered wheelchair and text-to-voice synthesizer where the patient can type words using EOG based keyboard and tell what he/she wants. EOG signals will be used to control the cursor of GUI and use voluntary blink patterns to detect "enter".

EOG signal are the primary input for tracking the eye movement and classify the direction in which the cursor should move, i.e. left, right, up, down or center.

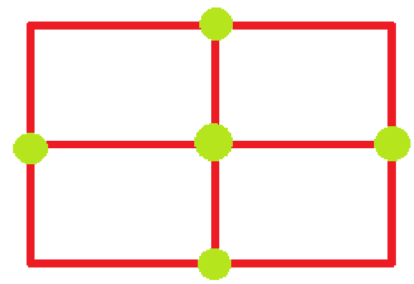

Fig. 1. Center points for regions of labels for eye movement

The diagram shows the 4 directions which will make 5 class labels including looking straight. In addition to these 5 labels, a 6th and 7th labels will be used for voluntary and involuntary blinking of eye and a separate rejection set will be introduced to detect any unwanted classification of random movement of eyes.

The EOG signals are first collected and pre-processed. The EOG signals first undergo filtering to remove the DC and 60Hz noise components. Then, Wavelet transformation and time domain analysis techniques are used as feature extraction techniques that are applied on the filtered signal to extract relevant information from the data for signal classification. Artificial Neural Network and Support Vector Machine have been explored in an attempt to identify a better classification algorithm for bio-signals.

II. LITERATURE SURVEY

In the recent years, Stationary Wavelet Transforms (SWT) has been extensively used for feature extraction and denoising in EOG signals [1-6]. In addition, there are some time domain feature extraction techniques such as maximum peak amplitude value (PAV), maximum valley peak value (VAV), thresholding and envelope filters to remove eye blinking [7, 8, 9, 10]. Conventional neural networks have long been used to successfully classify the EOG signals [11, 12]. However in a recent study, grey wolf optimization based neural network has been found to give better results than the conventional neural network [13]. Many studies have also been conducted on the effectiveness of Support Vector Machine (SVM) in classifying EOG signals. In one such study by Yurdagül Karagöz et al., they verified that SVM can be used for a similar application such as ours and it can give an accuracy of up to 92.6 % [14].

Next, we will explore some feature extraction techniques that are used in the study.

A. Wavelet Transform and Time Domain Analysis for pre-processing and feature extraction

EOG signals are very weak signals and contain a lot of high frequency noise. Stationary Wavelet Transform is generally used in denoising of the signal and feature reduction for EOG signal classification. Denoising of the signal gives us a much cleaner signal to work with and supresses the effects of a supervised learning algorithm to learn and model itself to the noise in the signal.

On the other hand, the time domain analysis - which may include maximum peak amplitude value (PAV), maximum valley amplitude value (VAV), thresholding on the time series signal, computing derivatives of the signal, applying envelope filter models, etc. - are used not only for feature extraction and feature reduction, but sometimes also for classification process of the EOG signals [15].

Stationary Wavelet Transform: The Discrete Wavelet Transform is a powerful tool for transient analysis for non-stationary waves like ECG and EEG signals. The Discrete Wavelet Transform (DWT) means choosing subsets of the scales ‘a’ and positions ‘b’ of the mother wavelet Ψ(t) [1].

$$\Psi_{a,b}(t) = 2^{\frac{a}{2}}\Psi(2^a t - b) \tag{1}$$

But due lack of translation invariance of DWT, it is not fit for stationary waves like EOG signals. Stationary wavelet transform (SWT) is an enhanced version of DWT, where the upsamplers and downsamplers have been removed and upsampling of the filter coefficients by a factor of $2^{(j-1)}$ in the j^{th} level of the algorithm [16]. This means that instead of using sub-sampling, SWT uses recursive dilated filters [1]. Fig. 2 shows the SWT decomposition scheme.

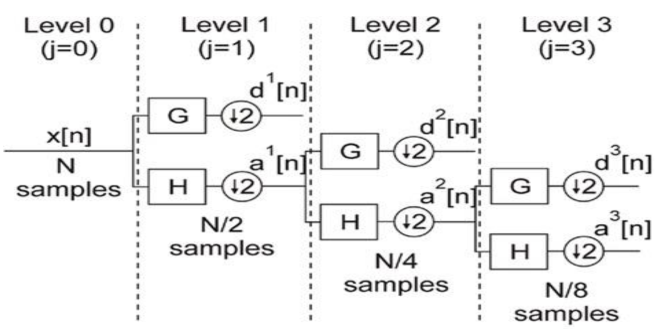

Fig. 2. Stationary Wavelet Transform decomposition scheme

Derivatives of the EOG signal: The derivative of a signal can be used to calculate the slope of the signal at any instance. There is a sudden spike in the EOG signal whenever there is any eye movement. The slope of these EOG spikes will be larger and thus it can give information about the movement of the eye. Derivate of a signal x(t) is given by (2).

$$x'(t) = \frac{x(t + \Delta t) - x(t)}{\Delta t} \tag{2}$$

where, $\Delta t \rightarrow 0$

Manuel Merino et al. gave a very detailed description about the derivatives of the EOG signal corresponding to different eye movement [17]. Fig. 3 shows EOG signal and its derivative.

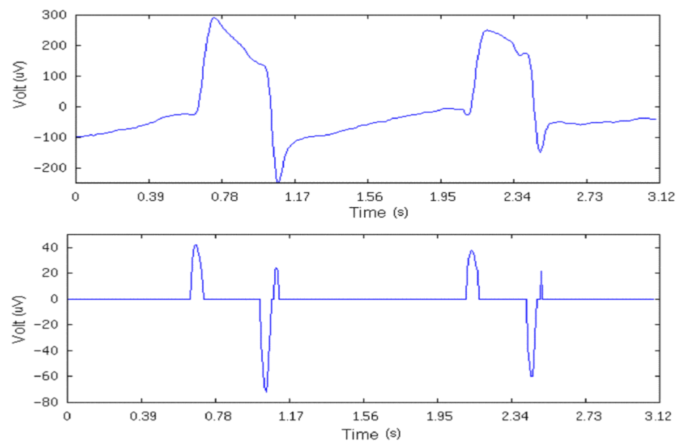

Fig. 3. (a) EOG signal; (b) Derivative of EOG signal

PAV & VAV: While collecting EOG signals, we only require two channels, one for the horizontal movement of the eye and one for the vertical movement of the eye. The EOG signal is the difference of action potentials generated between upper/lower eye muscle or left/right eye muscle when the eye moves in the corresponding direction. If the eye moves in horizontal direction, the first derivative of the signal on that channel will give a maximum peak for one direction and a maximum valley for the other direction. Thus the maximum peak amplitude value (PAV) and maximum valley amplitude value (VAV) gives us relevant information about the direction of movement of the eye [7, 8, 9, 10]. Fig. 4 shows PAV and VAV in an EOG signal. These features can be further used for thresholding and other classification schemes for recognizing the direction of eye movement.

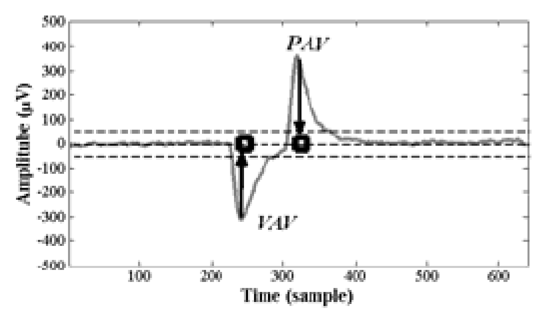

Fig. 4. Maximum peak amplitude value (PAV) and maximum valley amplitude value (VAV)

UWL & LWL: The involuntary blinking of the eye is much faster than voluntary movement of the eye. This difference between the voluntary movement and involuntary blinking of eye can be identified from the length of spike of the first derivative of the signal for the eye movement and eye blink [10]. Fig. 5 shows the Upper and lower wave length of the EOG signal for eye movement. This nature of the eye can be used to detect involuntary eye blink and remove this artifact.

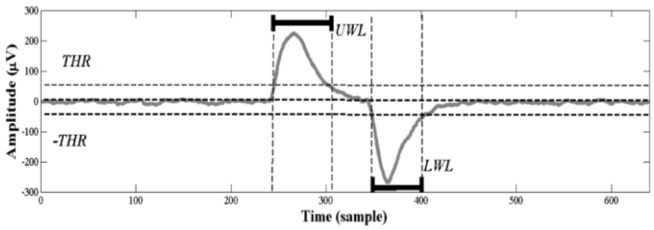

Fig. 5. Upper wave length (UWL) and Lower wave length (LWL)

Maximum global relative amplitudes on orthogonally decomposed signals: EOG signal is a bipolar signal which varies with the movement of eye contains information in time as well as frequency domain. Fourier Transform and Discrete Wavelet Transform can be used for frequency domain analysis. DWT gives better accuracy than FFT but DWT analysis degrades due to aliasing. In a recent study, a low computation cost method was proposed where the filtered signal is first normalized and then decomposed using two pairs of orthogonal signals. The maximum global relative amplitude and their locations in the orthogonally decomposed signals are then used as features for classification application [23]

Thus, we believe that Stationary wavelet transform and time domain analysis will help us extract maximum information from the EOG signals. In the next section, we will explore neural networks and support vector machine, which will be used as classification techniques for our project.

B. Neural Networks and SVM classifiers

In the past few years, neural networks and support vector machine are extensively used for the classification of EOG signals [11, 12, 13, 14]. The nature of our project demands a supervised learning classification algorithm that could recognize the eye movement based on the EOG signals. This could be achieved by using neural network and support vector machine.

Neural Networks: The artificial neural network is a supervised learning classification model which is based on the how human brain works. ANN contains various nodes in layers which forms a network, much like the brain neurons create a network. ANN acts like a black box and is an abstracted classifier. Neural Network works in two phases, i.e., learning phase and testing phase.

In learning phase, the neural network is modeled using supervised learning. The network is fed with input and corresponding output labels. Forward propagation is used to compute the output of the NN and compared with the known output to calculate the error. After this, back propagation is used to adjust the network weights to minimize the error. This is repeated for a large dataset so the network model is aligned to the dataset.

In the testing phase, only forward propagation is used to compute the output of the NN where the output is given by classifying the input to its corresponding label. Fig. 6 shows the neural network model with one input layer, one hidden layer and one output layer with two output labels.

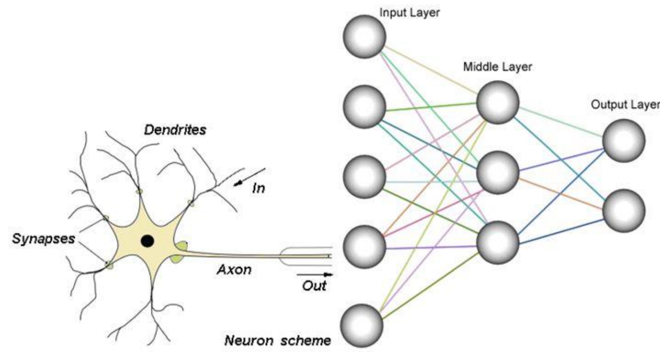

Fig. 6. Neural Network Model

In the recent studies, researchers are proposing modified and enhanced NN models collaborated with other classification methods to achieve better classification accuracy [13, 18, 19]. Such studies give us better methods of achieving higher classification accuracy in our project.

Support Vector Machine: Support vector machine is a supervised learning classification model, which, given the training examples each marked as belonging to one or the other class, classifies the new data into one of the two classes, making it a non-probabilistic binary linear classifier. The SVM can also perform non-linear classification efficiently using "kernel trick". With the help of kernels, the inputs can be mapped into higher dimensional feature spaces to perform non-linear classification.

SVM is binary classifier, i.e., it can only classify an input in one of two labels. Thus, one-vs-all scheme is used for more than two classes. The output of the kernelized SVM is given by (4) [20].

$$f(x) = \sum_{i=1}^{N} \alpha_i d_i k(x_i, x) + b \qquad (3)$$

$$d(x) = sgn(f(x)) \qquad (4)$$

Here, N is the number of training samples; b is the threshold; α_i is the Lagrange multiplier; d_i is the output of i^{th} training sample and $k(x_i, x)$ is the kernel function. Fig. 7 shows a kernelized SVM model.

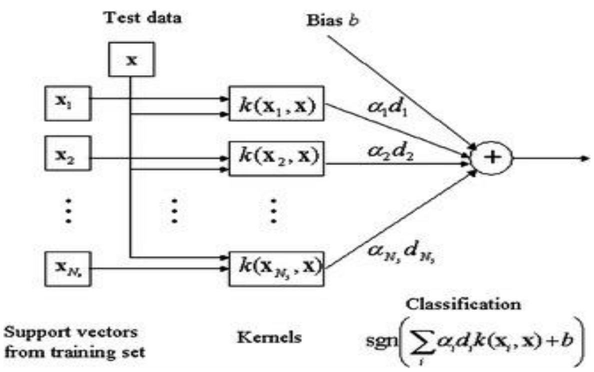

Fig. 7. Kernelized Support Vector Machine (SVM) model

Appropriate kernel function must be selected so that the SVM model can train to the given dataset. Lou XIONGWEI et al. discusses about the kernel selection and construction for SVM classifiers [21].

Next we will provide details of our approach for the project.

III. Approach

A Graphical user interface has been designed on MATLAB. Fig. 8 shows the designed GUI for the project. The GUI consists of a visual keyboard where the yellow box indicates the current position of the cursor. Based on the EOG signals feed as input, the cursor can be moved in left, right, up or down direction and a voluntary blink can be used as a key press. The system has been implemented using two classification models, that is, Support Vector Machine (SVM) and Neural Networks (NN). The user can feed in any string and finally feed enter to indicate the GUI to push the string into a text to speech convertor.

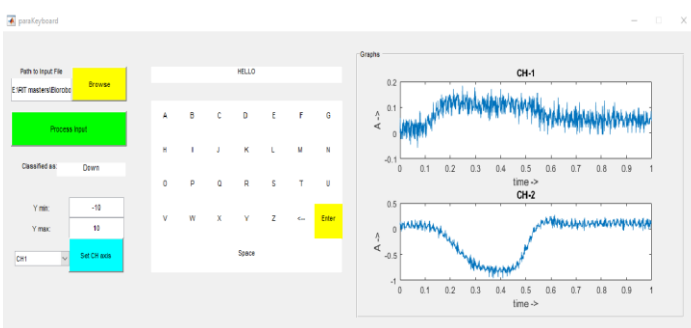

Fig. 8. MATLAB GUI for EOG based HCI

Data Collection and pre-processing: EOG signals are the difference of action potentials generated between upper/lower eye muscle or left/right eye muscles when the eye moves in the corresponding direction. For this, we have two channels to record the bio-signals, one for horizontal direction and one for vertical direction. BioCapture software is initially used to program the BioRadio150 to set the sampling frequency to 960 Hz and 16 bit resolution. The MATLAB SDK provided by CleveMed is used to record the EOG signals online directly on MATLAB and further processed [22]. The GUI shows the signal received from the channels in one window and the Keypad in the middle. Fig. 9 shows the placement of electrodes for EOG signal collection.

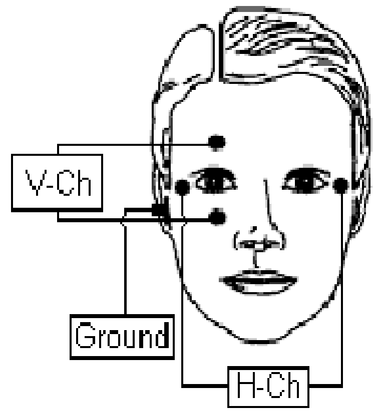

Fig. 9. Electrode placement for collecting EOG signals

The data from the BioRadio150 is first filtered to remove the 60Hz noise. A level 6 stationary wavelet transformation (SWT) decomposition using Daubechies wavelet is applied to the filtered data for signal denoising. Following the denoising process, the DC component is removed from the signal using equation (5) [23].

$$x(t) = x(t) - mean[x(t)] \quad (5)$$

Following is an example of feature extraction for an EOG sample for Up movement of eye. Fig. 10 shows denoising of the signal.

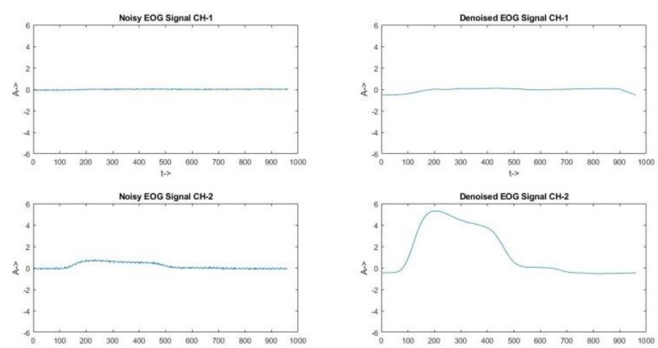

Fig. 10. Denoising of EOG sample

After filtering and cleaning the EOG signals, the collected samples are stored with different labels for training the classifiers, which we will discuss next.

Feature Extraction and classification: In this project, a greater emphasis is given to the feature extraction techniques. After we collect and pre-process the EOG signal data, next we extract features from the EOG signal which will act as attributes that we can use to model our classifiers and classify the EOG signals later.

After denoising of the EOG signal, the signal becomes much cleaner to work with and it can give much accurate results. Next the signal is differentiated to calculate the slope of the signal. The slope of the signal contains lots of information like the direction of eye movement, the velocity of eye, etc. We are extracting features like Peak Amplitude Value (PAVP, Valley Amplitude Value (VAV), Upper Wavelength (UWL) and Lower Wavelength (LWL). Fig 11 shows the derivative of the denoised signal. Fig 12 and 13 shows extraction of features from the differentiated signal from channel 1 and channel 2 respectively.

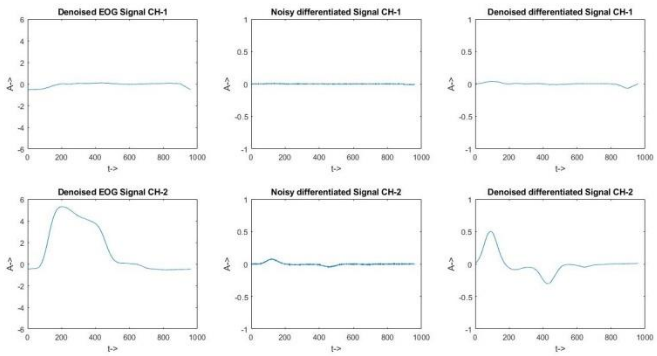

Fig. 11. Derivative of the denoised EOG signal

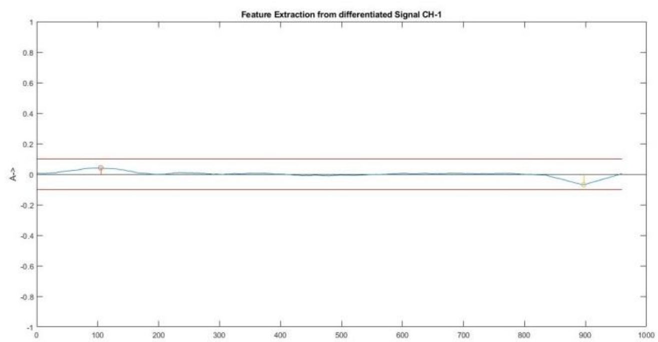

Fig. 12. Feature extraction from channel 1

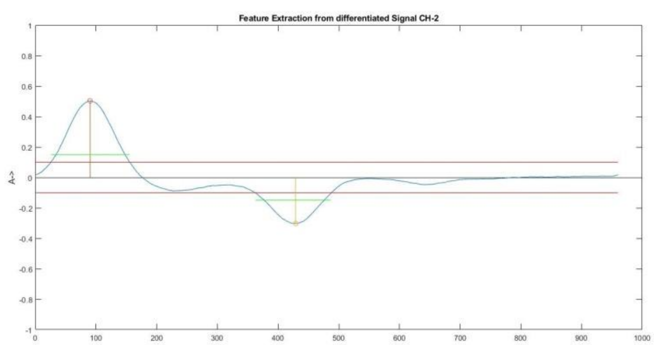

Fig. 13. Feature extraction from channel 2

Features are also extracted by taking maximum global relative amplitude on orthogonally decomposed signals. The signal is decomposed by using concatenating the signals from the two channels and multiplying them with decomposition templates where decomposition templates are taken as two pairs of orthogonal signals. Fig. 14 and 15 shows the decomposition templates and decomposed EOG signals respectively.

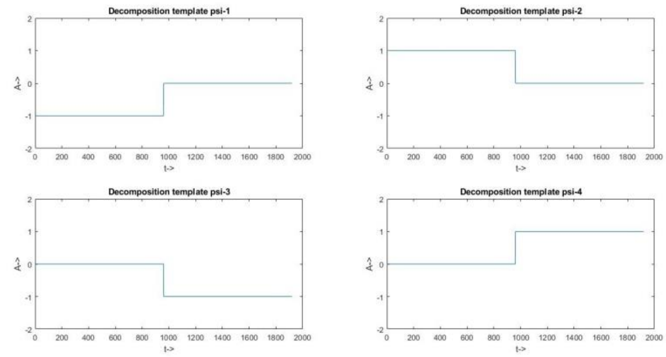

Fig. 14. Decomposition templates (two pairs of orthogonal signals)

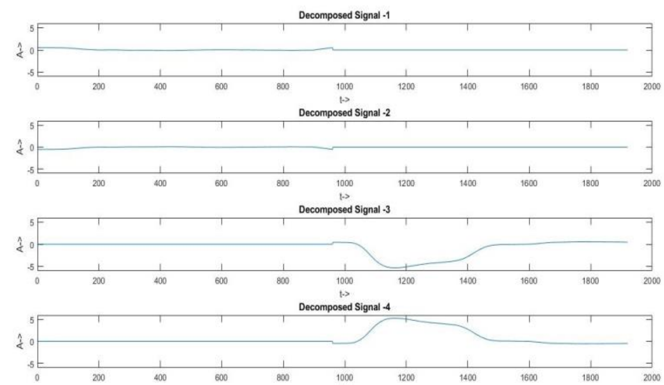

Fig. 15 Orthogonally decomposed EOG signals

These orthogonally decomposed signals are concatenated together to get a final decomposed signal. Global maximum and argument of global maximum are computed and taken as features. This technique of feature extraction is discussed in detail in a recent study [23]. Fig. 16 shows the feature extraction from the orthogonally decomposed EOG signal.

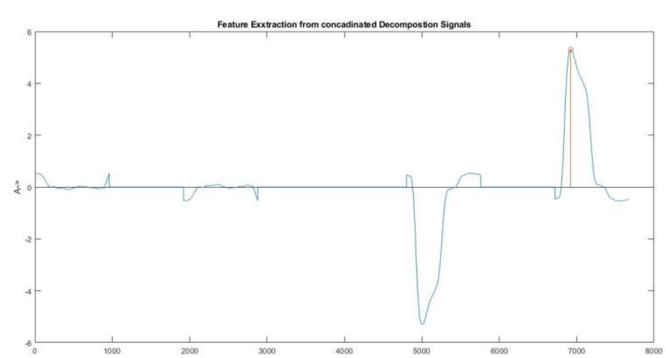

Fig. 16. Feature extraction from orthogonally decomposed EOG signal

The project has been successfully implemented using two classification techniques, SVM and neural networks. For implementation with support vector machines, one-vs-all classifier is used, i.e., 8 different binary SVM models are trained using Gaussian kernels, one for each class. Fig. 17 shows how one-vs-all technique is implemented using binary class SVM by taking an example of 'Up' sample.

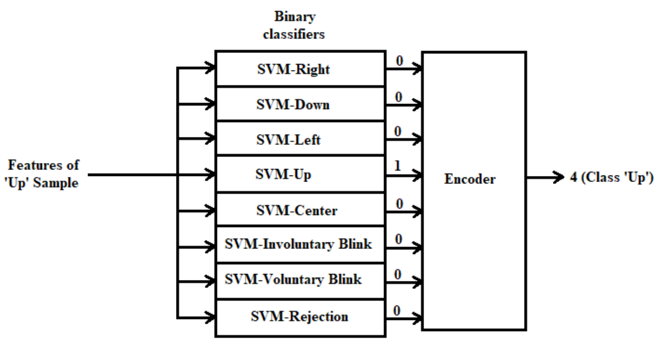

Fig. 17. Multiclass classification using one-vs-all technique with SVM

For multiclass classification using a binary classifier like SVM, a technique called one-vs-all or one-vs-rest is used. In this, one separate SVM model is trained for each class such that it treats the samples of that class as one class and the samples of all the other classes as the other class.

For implementation with neural networks, a cascaded feed-forward network has been used with 10 nodes in input layer, 30 nodes in the hidden layer and 8 nodes in output layer for each class label, i.e., Up, Down, Left, Right, Voluntary Blink, Involuntary Blink, center and rejection class. Fig. 18 shows the structure of the neural network model.

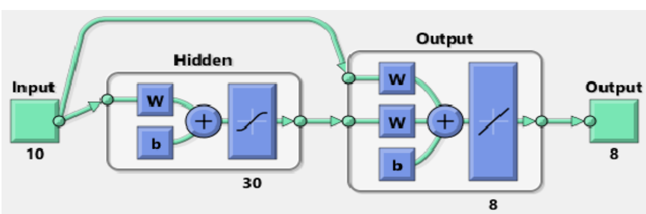

Fig. 18. Cascaded feed-forward neural network model

Fig. 19 shows the data flow diagram for our project while training and testing. First, the EOG signals are collected, filtered and pre-processed. The processed signals are then used to extract the features for training classifier. In the testing phase, the EOG signals are filtered pre-processed and features are extracted from the signal. These features are fed to the already trained classifier to classify the signal to one of the output labels and recognize what kind of eye movement occurred. Based on the eye movement, the EOG based keyboard GUI responds accordingly with the cursor moving in the desired direction.

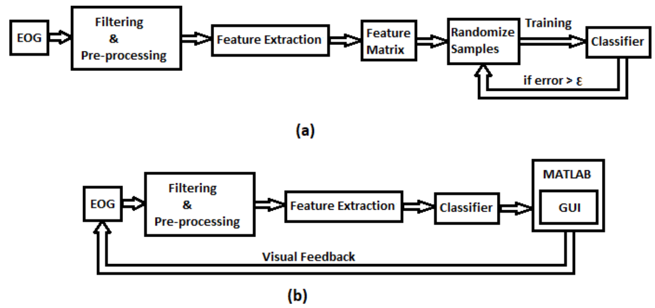

Fig. 19. (a) Data Flow Diagram for training classifier; (b) Data Flow Diagram for the project during testing

IV. RESULTS

It has been observed that the EOG signals can be successful quantified into different eye movements with a high success rate. It was observed that the SVM model performs best with a Gaussian kernel and worst with a linear SVM model. Similarly, a cascaded feed forward neural network performs slightly better than a feed forwarded NN. Table 1 sum up the performance of various algorithms on a test and training sets.

Tabel. 1. Performance measure of various algorithms on training and test set

Algorithm	**Accuracy on Test set**	**Accuracy on Training set**
SVM with linear Kernel		
SVM with polynomial Kernel		
SVM with Gaussian Kernel		
Feed Forward Neural Network		
Cascaded Feed Forward NN		

V. CONCLUSION

In conclusion, various feature extraction and classification techniques were explored and successfully used to implement an EOG based HCI to control a cursor on a GUI with a text to speech convertor. Similarly, EOG signals can be used to have paralysis patients with normal functioning eyes to control their environment to some extent with the aid of technology. Neural Networks seem to be performing better than Support Vector Machine in terms of classification accuracy but are computationally more expensive to train.

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