Comparison of ANN and SVM for classification of eye movements in EOG signals

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Abstract. Nowadays, electrooculogram is regarded as one of the most important biomedical signal in measuring and analyzing eye movement patterns. Thus, it is helpful in designing EOG-based Human Computer Interface (HCI). In this research, electrooculography (EOG) data was obtained from five volunteers. The (EOG) data was then preprocessed before feature extraction methods were employed to further reduce the dimensionality of data. Three feature extraction approaches were put forward, namely statistical parameters, autoregressive (AR) coefficients using Burg method, and power spectral density (PSD) using Yule-Walker method. These features would then become input to both artificial neural network (ANN) and support vector machine (SVM). The performance of the combination of different feature extraction methods and classifiers was presented and analyzed. It was found that statistical parameters + SVM achieved the highest classification accuracy of 69.75%.

1. Introduction
In recent years, there is growth in interest among researchers in pattern recognition, which is a study of how machines, instead of human can learn and identify patterns (classes) of interest, and make precise decision on the classes identified [14]. Pattern recognition has been applied in numerous scientific and engineering disciplines such as biology (medical diagnosis), artificial intelligence (AI), remote sensing and etc. HCI, which is based on pattern recognition is helpful in assisting users with various tasks. The research on HCI can greatly improve the quality of life, especially for those severely disabled person that suffer from spinal cord injuries, Locked-in Syndrome, muscular dystrophy, Amyotrophic Lateral Sclerosis (ALS) and etc. These patients have difficulty in conveying their intentions because they lack control of their voluntary muscle. However, they are still conscious and are able to control their eye movements.

There are several devices that are used to record activities of human eyes, however most of them have their own limitations. Video-oculography is costly, and has to be calibrated repeatedly to obtain accurate measurements [10]. Magnetic search coil, being another eye tracking device can cause irritation and discomfort to subjects because magnetic search coil has to be inserted into a subject’s eye. In view of this, EOG signals can be another feasible alternative. EOG is measure of changes in corneo-retinal potential (CRP) according to eye movement. This potential difference arises from positive poles of cornea and negative poles of retina. Due to its relatively larger amplitude reading compared to other biomedical signals like electroencephalogram (EEG) and electromyogram (ECG), EOG signals is easier to be recorded. Therefore, EOG is a good candidate to be chosen as the input of eye movement classification system despite the fact that EOG is seldom deterministic. In fact, many HCIs using EOG
as input have been proposed such as electrical wheelchair control [5], mobile robot control [17], eye writing recognition [1] [24], activity recognition [7] and so on.

As for the classification scheme, two of the most popular classification models, ANN and SVM were employed in this study. ANN can be defined as computing model that originated from the understanding of the structure and function of biological neural networks. ANN can be configured for specific mathematical purposes like data classification, curve fitting, mathematical modeling and etc. On top of that, ANN is able to derive relations between inputs and outputs which are too complex for human. Nowadays, ANN is a very important and flexible classification algorithm in designing novel pattern recognition systems.

SVM is another classifier that has been studied extensively after its introduction by Bernhard E. Boser et al. at COLT-92 conference [6]. Originally, it was designed for binary classification problem. SVM is famous for its excellent classification performance in various applications. It is not affected by the curse of dimensionality, which means it can handle large dimension input variables classification problems by projecting the input data into higher dimensional space. In addition, tradeoff between classifier complexity and error can be adjusted explicitly by manipulating certain parameters.

The primary motivation of this study is to assess and compare the performance of different classifiers (ANN and SVM) in terms of classification accuracy and training time. This study also explores different types of feature extraction method on the preprocessed EOG signals. It is hope that this paper can help in development of robust and user friendly algorithm for classification of EOG signals.

2. Materials and Methods

2.1. Data Acquisition
EOG signal was collected from 5 volunteers with the age in between 22 and 26. The details of the 5 subjects are listed in Table 1. EOG measurements were taken using Biopac MP36R data acquisition unit. The sampling rate is set to be 100 Hz for both channels.

| Subjects | Ages | Gender | Vision |
|----------|------|--------|--------|
| 1        | 24   | Male   | Glasses|
| 2        | 25   | Male   | Normal |
| 3        | 25   | Female | Glasses|
| 4        | 26   | Male   | Glasses|
| 5        | 22   | Male   | Normal |

(1) Before the start of the experiment, subjects were instructed to perform eye movements until they are familiar with the tasks. The subjects was asked to stay relaxed sitting on a chair. Disposable lead electrodes were attached to positions around the eyes as shown in Figure 1.
Figure 1. Placement of surface EOG electrodes. Ch. V+ and Ch. V- measure the vertical eye movement, while Ch. H+ and Ch. H- measure the horizontal eye movement.

(2) A simple eye movement interface using animation features of Microsoft Power Point 2013 was designed prior to the experiment. Before the start of the recording of EOG signals, subjects were instructed to keep their eyes on the ball that appear on the laptop screen. The ball followed the movement as illustrated in Fig. 2. Each eye movements (target actions) was repeated for 5 times per session. A total of 10 session was conducted for each subject. The participants were asked to blink only when the ball was at its central position. During the experiment, the eyes position was aligned with the central position of the ball and the distance was fixed at 30 cm.

Figure 2. The ball will move downwards in 1 second and back to its original central position in 1 second. The ball will be stationary at the central position for 5 seconds before moving upwards according to the order shown by the circled numbers. This cycle will repeat 5 times each session. 10 session were conducted for each subjects.

(3) Data preprocessing, feature extraction and supervised classification algorithm thereafter was performed with the aid of Matlab (R2013a).

2.2. Data Preprocessing
EOG signals are frequently contaminated with noises and other interferences, such as eye blinks, powerline interference, head movements and so on. Knowing that the effective EOG signals is in between 0.1Hz (DC)-50Hz, Chebyshev 4th order bandpass filter of the particular frequency range was used. This is to attenuate and simultaneously suppress power supply interference. The baseline of raw EOG signals is removed using:

\[ X_i = S_i - \mu(x) \]  \hspace{1cm} (1)

where \( \mu(x) \) is the mean of raw EOG signal, \( S_i \) is EOG signal data points.

The EOG signals is normalized after baseline removal. The normalization is carried out with the following formula:
Figure 3 shows the EOG signals before and after preprocessing.

![Figure 3. Before (left) and after preprocessing (right) of EOG signals. (Source: subject 1 session 1).](image)

2.3. Feature Extraction

Classification using raw EOG signals would be time consuming and ineffective because of the signal noise originated from eye blinks, EMG from facial response, incorrect electrodes placement, influence of luminance and etc. Another major drawback would be high computational cost due to enormous input data size. Nonetheless, EOG signals can be represented by means of some attributes. Such attributes can be used as features to characterize the signals. The method to obtain these features is called feature extraction. Feature extraction is pivotal in deriving unique pattern from the original dataset without loss of key information. In other words, feature extraction reduces dimensionality of data but maximizes inter-class separability and intra-class similarity at the same time. In the present work, statistical features [23], AR coefficients derived from Burg method and PSD estimation using Yule-Walker method [3].

2.3.1. Statistical Parameters. The following ten statistical features of each EOG channels (horizontal & vertical eye movement) are used as parameters to characterize the EOG signals:

i) Minimum, $x_{min}$

ii) Maximum, $x_{max}$

iii) Mean

iv) Median

v) Mode

vi) First quartile

vii) Third quartile

viii) Interquartile range

ix) Standard deviation

\[ S = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N - 1}} \]  

(3)

x) Kurtosis coefficients

\[ k = \frac{E(x - \mu)^4}{\sigma^4} \]  

(4)
2.3.2. Autoregressive (AR) model coefficients derived using Burg algorithm. In an AR model, the variable of interest is predicted using linear combination of past values of the variable. It is commonly used to model time series data. The AR model of order k, AR(k) is as follow:

\[
x_t = \sum_{i=1}^{k} a_i x_{t-i} + \varepsilon_t
\]

where \( a_i \) are AR coefficients, \( x_t \) is the output of AR model, \( x_{t-i} \) is the previous known data points, \( \varepsilon_t \) is the residual term, or so called Gaussian white noise. In order to estimate \( a_i \), Burg method \([8]\)was utilized. In this paper, AR(4) model is chosen

2.3.3. Parametric Power Spectral Density (PSD) Estimation using Yule-Walker method. Parametric or model based method of spectral estimation assume that the signal can be estimated by model with known functional form. Once the coefficients in the assumed model can be estimated with certain algorithm, the signal’s spectral characteristics are then derived from the estimated model. Common models available are AR model, moving average (MA) model, and autoregressive moving average (ARMA) model. Since AR model is appropriate in representing spectra with narrow peaks \([25]\), so AR(4) model is chosen and Yule-Walker method is used to estimate the coefficients by solving equation (7).

\[
\begin{pmatrix}
x(0) & \cdots & x(-n+1) \\
\vdots & \ddots & \vdots \\
x(n-1) & \cdots & x(0)
\end{pmatrix}
\begin{pmatrix}
a_1 \\
\vdots \\
a_n
\end{pmatrix}
=
\begin{pmatrix}
x(1) \\
\vdots \\
x(n)
\end{pmatrix}
\]

The power spectral density, \( S_x(f) \) of the time series, \( x_t \) is given in equation (8).

\[
S_x(f) = |H(f)|^2 S_e(f) = \frac{1}{f_s} \frac{\sigma^2}{|1 - \sum_{i=1}^{k} a_i e^{-j(2\pi)f}t|^2}
\]

where \( H(f) \) is the transfer function where \( a_i \) are estimated by Yule-Walker equation, \( S_e(f) \) is power spectrum of white noise with variance, \( \sigma^2 \) and sampling frequency, \( f_s \). In this paper, I used 65-point discrete approximation of the power spectrum.

2.4. Eye Movement Classification using ANN

ANN has already achieved a huge number of practical applications \([18][22][4]\). ANN is more superior to other artificial intelligence (AI) system because it is flexible and adaptive which means the network can adjust itself to new environment. Another justification for this is ANN user does not need to have access to domain-specific knowledge. However, ANN algorithm is iterative, which can sometimes suffer from convergence problem. In this research, multilayer feedforward ANN \([15]\) is chosen because it is suitable for classification problem where supervised learning is implemented with Levenberg-Marquardt (LM) algorithm \([12]\). ANN was implemented in Matlab version R2013a with neural network toolbox.

There are two main steps in the algorithm of feed forward ANN. First, the neurons (processing units) calculate the weighted sum of its inputs and then apply activation function to this sum to derive its outputs \([21]\). Second, ANN will undergo backpropagation. The purpose behind this step is to adjust the connection weights of multilayer perceptron (MLP) based on the errors of outputs produced. An MLP consists of three layers: input layer, hidden layer and output layer. Each layer is composed of predefined number of neurons. Figure 4 shows basic architecture of multilayer feed forward ANN. Figure 5 shows Matlab generated schematic diagram of neural network when statistical parameters is the input.
2.5. *Eye Movement Classification using SVM*

Undoubtedly, SVM is an effective classification algorithm in various research fields. Its application encompasses text categorization [16], face detection [11], diagnosis of breast cancer [20] and etc.

So, how SVM works? SVM is a binary classifier that tries to find the optimal hyperplane. Optimal hyperplane means a linear decision surface that splits n-dimensional space ($\mathbb{R}^n$) into two parts and simultaneously the distance of decision boundary from the data of both classes should be as far away as possible. This is shown schematically in Fig. 6.

With the introduction of slack variables and kernel functions, SVM can be applied in non-linearly separable problem with high dimensional input data. In this study, the following SVM formulation will be used:

Training phase:

\[
\text{minimize} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{n} \alpha_i \\text{subject to } 0 \leq \alpha_i \leq C, C > 0 \text{ (user-defined parameter)}
\]

Testing phase:

Classify the unseen objects, $x$ using the function below:
\[ f(x) = \text{sign} \left( \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b \right) \]  

The SVM algorithm is carried out in MATLAB (R2013a) using LIBSVM (version 3.20) package available at http://www.csie.ntu.edu.tw/~cjlin/libsvm/. Radial Basis Function (RBF) was chosen for classification because it is widely used and usually the first choice compared to other kernel functions in the literature [9].

3. Results and Discussions

3.1. Construction of different feature sets
Out of 10 sessions of EOG reading for each subject, last 3 sessions of the EOG signals are selected as the testing data. The remaining seven are used as the training data. Different features are extracted from these data. The dimension of training dataset and testing dataset is shown in Table 2. The training vectors are used to train ANN and SVM classifiers, whereas the accuracy and efficacy of the trained models were evaluated using testing vectors.

| Table 2. Dimensions of training and testing data for different feature extraction methods. |
|--------------------------------|------------------|------------------|
| Feature extraction methods       | Training data    | Testing data     |
|---------------------------------|------------------|------------------|
| Statistical parameters           | 120x20           | 80x20            |
| AR coefficients                  | 120x10           | 80x10            |
| PSD features                     | 120x130          | 80x130           |

3.2. Comparison between ANN and SVM
In this paper, the performance of classifiers is evaluated subject by subject. Performance evaluation and comparison is presented with the use of testing accuracy and training time. The classification accuracy is calculated as proportion of actual positives which are predicted positive [2]:

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

where \( NT \) is the number of trials with true prediction and \( NF \) is the number of trials with false prediction.

Based on the results from Table 3 to Table 8, under the same features data as input, both classifiers produces roughly similar results. ANN is slightly better than SVM in terms of classification rate when AR and PSD features were used, but takes longer training time. On the other hand, SVM outperforms ANN in both aspects when statistical parameters was used. When classification accuracy of the three methods are compared, statistical method achieves the best accuracy: 66.5\% (ANN), 69.75\% (SVM), in contrast with AR coefficients accuracy: 54\% (ANN), 53.75\% (SVM) and PSD accuracy: 50.25\% (ANN), 49\% (SVM). It can be seen from the table that SVM with statistical parameters as the input produces the best results, with accuracy of 69.75\% and fairly low training time of 0.158s.

In terms training time of both classifiers, SVM outperforms ANN in multiclass classification. This can be explained by how classification model is trained under SVM. As a robust supervised learning algorithm, SVM attempts to maximize the distance (margin) between the closest training points (support vectors) from either class in order to achieve better generalization performance on test data [13]. The solution is based on support vectors. Thus, it reduces the number of operation needed to compute a model (not all features vector is included in the calculation). Unlike SVM, the central idea of ANN is to sum up linear combinations of all input data and bias value in each neuron, and then model the output as a nonlinear function of these summation values, which increases the number of operation as well as computational complexity and cost. Fig. 6 and Fig. 7 shows the summary of results in terms of classification accuracy and training time.
Table 3. Classification results for statistical parameters as features using ANN as classifier.

| Subjects | Classification accuracy (%) | Overall classification accuracy (%) | Duration for training (s) |
|----------|-------------------------------|------------------------------------|--------------------------|
|          | Down\(^a\) | Up\(^b\) | Left\(^c\) | Right\(^d\) | |
| 1        | 55       | 65     | 90       | 90       | 75       | 1.161 |
| 2        | 30       | 60     | 45       | 80       | 53.75    | 0.412 |
| 3        | 70       | 50     | 45       | 85       | 62.5     | 0.611 |
| 4        | 85       | 85     | 65       | 75       | 77.5     | 0.445 |
| 5        | 35       | 70     | 75       | 75       | 63.75    | 0.407 |
| Mean     | 55       | 66     | 64       | 81       | 66.5     | 0.607 |

Note:
Down\(^a\) represents event which eyes move centre-down-up.
Up\(^b\) represents event which eyes move centre-up-down.
Left\(^c\) represents event which eyes move centre-left-right.
Right\(^d\) represents event which eyes move centre-right-left.

Table 4. Classification results for statistical parameters as features using SVM as classifier.

| Subjects | Classification accuracy (%) | Overall classification accuracy (%) | Duration for training (s) |
|----------|-------------------------------|------------------------------------|--------------------------|
|          | Down\(^a\) | Up\(^b\) | Left\(^c\) | Right\(^d\) | |
| 1        | 55       | 85     | 95       | 95       | 82.5     | 0.129 |
| 2        | 45       | 90     | 30       | 80       | 61.25    | 0.129 |
| 3        | 40       | 85     | 65       | 80       | 67.5     | 0.142 |
| 4        | 90       | 85     | 50       | 85       | 77.5     | 0.247 |
| 5        | 60       | 50     | 55       | 75       | 60       | 0.144 |
| Mean     | 58       | 79     | 59       | 83       | 69.75    | **0.158** |

Table 5. Classification results for AR coefficients as features using ANN as classifier.

| Subjects | Classification accuracy (%) | Overall classification accuracy (%) | Duration for training (s) |
|----------|-------------------------------|------------------------------------|--------------------------|
|          | Down\(^a\) | Up\(^b\) | Left\(^c\) | Right\(^d\) | |
| 1        | 75       | 80     | 75       | 30       | 65       | 0.355 |
| 2        | 40       | 60     | 65       | 70       | 58.75    | 0.296 |
| 3        | 20       | 55     | 70       | 25       | 42.5     | 0.345 |
| 4        | 60       | 55     | 60       | 50       | 56.25    | 0.309 |
| 5        | 65       | 15     | 60       | 50       | 47.5     | 0.323 |
| Mean     | 52       | 53     | 66       | 45       | 54       | 0.326 |

Table 6. Classification results for AR coefficients as features using SVM as classifier.

| Subjects | Classification accuracy (%) | Overall classification accuracy (%) | Duration for training (s) |
|----------|-------------------------------|------------------------------------|--------------------------|
|          | Down\(^a\) | Up\(^b\) | Left\(^c\) | Right\(^d\) | |
| 1        | 80       | 80     | 60       | 50       | 67.5     | 0.115 |
| 2        | 30       | 70     | 75       | 50       | 56.25    | 0.091 |
| 3        | 20       | 60     | 45       | 45       | 42.5     | 0.058 |
| 4        | 60       | 25     | 35       | 70       | 47.5     | 0.248 |
| 5        | 65       | 35     | 70       | 45       | 53.75    | 0.246 |
Table 7. Classification results for PSD as features using ANN as classifier.

| Subjects | Down | Up  | Left | Right | Overall classification accuracy (%) | Duration for training (s) |
|----------|------|-----|------|-------|-------------------------------------|--------------------------|
| 1        | 50   | 75  | 15   | 90    | 57.5                                | 6.519                    |
| 2        | 75   | 35  | 20   | 90    | 55                                  | 5.124                    |
| 3        | 50   | 90  | 50   | 40    | 57.5                                | 4.121                    |
| 4        | 75   | 30  | 50   | 25    | 45                                  | 5.05                     |
| 5        | 45   | 30  | 25   | 50    | 36.25                               | 3.871                    |
| Mean     | 59   | 52  | 32   | 59    | 50.25                               | 4.937                    |

Table 8. Classification results for PSD as features using SVM as classifier.

| Subjects | Classification accuracy (%) | Overall classification accuracy (%) | Duration for training (s) |
|----------|-----------------------------|-------------------------------------|--------------------------|
| 1        | 80  45  60  55              | 60                                  | 0.066                    |
| 2        | 30  80  60  45              | 53.75                               | 0.056                    |
| 3        | 20  65  50  45              | 45                                  | 0.065                    |
| 4        | 45  45  30  55              | 43.75                               | 0.082                    |
| 5        | 80  50  10  30              | 42.5                                | 0.129                    |
| Mean     | 51  57  42  46              | 49                                  | 0.080                    |

![Classification accuracy of different feature inputs and classifiers.](image)
Figure 7. Training time of different feature inputs and classifiers.

Various approaches and findings and their respective classification accuracies for different types of eye movements have already been presented in the literature. Anwashe et al.10 achieved 80% classification accuracy for six types of eye movements by using AR+PSD as input for feed forward neural network. In Deng et al.2 work, 90% of accuracy was achieved for four directional eye movements using fuzzy distinction rule. Merino et al. proposed an algorithm that works with derivative and amplitude level and obtained 94% accuracy [19].

4. Conclusion
EOG signals have huge potentials to be applied in communication support system, such as eye-controlled wheelchair, virtual keyboard and etc. Features extracted from dataset plays vital role in the subsequent classification stage of EOG signals. This paper has taken into account some strategies to improve the analysis and classification EOG signals.

The introduced method of extracting statistical parameters from the time series of EOG data was found to be superior to other alternatives (AR coefficients and PSD features) regarding classification accuracy. PSD estimation is not a good feature extraction method, compared to other feature extraction method. This finding actually contradicts with the work of Anwashe et al.10 The combination of statistical feature extraction method and SVM was proved to be better than using ANN as classifier due to high generalization performance of SVM with classification accuracy of 69.75% and lower training time.

Future research will be focused on more combination of feature extraction methods and classifiers. State-of-the-art feature extraction algorithm like discrete wavelet transform (DWT) and newly emerged classifiers such as Extreme Learning Machine (ELM) can be good options for the improvement of the classification accuracy and training time.

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