Eye Blink Classification for Ear EEG

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by Carolyn Schwendeman

Research Project

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Abstract

Electroencephalography (EEG) is a safe, non-invasive method of monitoring the brain's electrical activity that can be used for Brain Computer Interfaces (BCIs). However, the usability of EEG in everyday BCIs is limited since clinical EEG systems consist of wet electrodes that must be placed across the scalp by a trained technician. Recently, it has been demonstrated that EEG signals may be recorded from dry electrodes placed inside the ear canal (in-ear EEG), yet in order to perform the signal classification necessary for BCIs these systems must overcome the challenges of reduced spatial covering and reduced SNR of the recorded EEG signals. In this technical report, a wireless, multielectrode, user-generic Ear EEG system is used to record voluntary eye blink events. Though eye blinks are an ocular artifact in EEG signals, eye blink event classification is a component of many EEG-based BCIs allowing for user choice selection and drowsiness detection. Here, classification of this signal is demonstrated with four machine learning classifier models: logistic regression, support vector machine, random forest, and an artificial neural network. A combination of temporal, spectral, and spatial features available to the Ear EEG system are implemented and analyzed in order to optimize classification results across these models and demonstrate the feasibility of more complex signal classification with in-ear EEG recordings. The result of this work is a comparison of four eye blink classifiers for the Ear EEG system each with sensitivity above 95% and specificity above 98%. The model that achieves the highest eye blink classification results is a random forest classifier with 100% sensitivity and 99.5% specificity.

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Chapter 1

Introduction

Electroencephalography (EEG) is used extensively in the clinical setting to monitor the electrical activity in the brain of a patient and diagnose neurological complications including epilepsy and sleep disorders [1] [2]. Additionally, the non-invasive nature of EEG make it an ideal tool for Brain Computer Interfaces (BCI). EEG systems may be used to record steady-state visual and auditory evoked potentials, event related auditory and visual potentials, low-frequency neural waves, and electrooculogram (EOG) related artifacts including eye blinks [3]. Many of these signals are practical for BCIs, which has led to work focusing on the development of EEG signal classifiers and detection algorithms.

Eye blink classification for EEG systems is used extensively in the clinical setting and is a fundamental component of many EEG-based BCIs. In the clinical setting, eye blink artifacts contaminate a recorded EEG signal and may interfere with the analysis of the signal for diagnostic purposes. Automated eye blink artifact removal techniques have been developed where the first stage of the algorithm focuses on the detection of the artifacts in the recorded EEG signal [4]. For BCIs, voluntary eye blink classification has been used for choice selection, cursor movement, and prosthetic control [5] [6] [7].

Additionally, it has been demonstrated that eye blink artifacts are a meaningful data feature to consider for drowsiness detection [8].

Until recently, EEG for consumer BCIs has been out of reach due to the extensive clinical set up an EEG system requires, the bulkiness of these systems, and the time limitations wet electrodes place on the recording of EEG signals. Clinical EEG utilizes wet electrodes that must be placed across the scalp by a trained technician [9]. The hydrogel of wet electrodes greatly reduces the electrode-skin impedance (ESI) and provides mechanical stability; however, as this hydrogel dries out the signal-to-noise ratio (SNR) of the system degrades which reduces the quality of the recorded signal [10]. EEG headsets that utilize dry electrodes have proven useful for ambulatory recording over longer periods of time, but the bulkiness of these headsets makes them not ideal for consumer BCI applications [11] [12].

Recently, it has been demonstrated that EEG can be recorded by dry electrodes from inside the ear [13]-[16]. Our work has demonstrated that a user-generic earpiece can be fabricated with low-cost and scalable manufacturing techniques. These earpieces can be employed to record voluntary eye blink artifacts, alpha band modulation, and auditory steady-state response EEG signals from within the ear using a wireless, multichannel read-out system [17] [18].

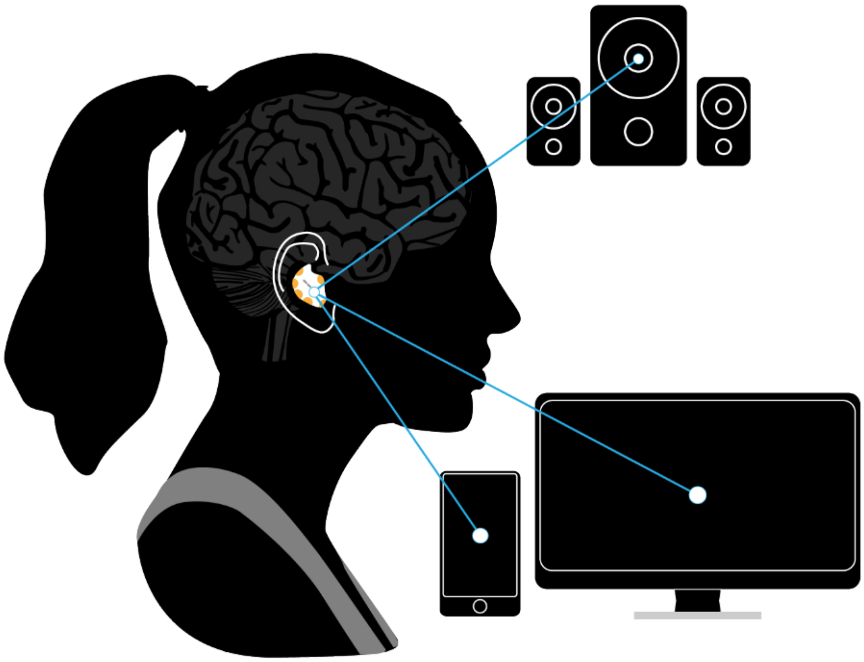

Fig. 1.1. Envisioned In-Ear EEG system for BCI

The discreet nature of an in-ear EEG system and the advancement towards a user-generic recording device are promising steps towards EEG for consumer BCIs (Fig. 1.1). However, in-ear EEG systems do not provide the same spatial covering as an EEG headset, and the use of dry electrodes may be less mechanically stable and reduce the SNR [12]. These differences between clinical and in-ear EEG systems present challenges for the implementation of signal classification for BCIs, since many EEG-based classifiers utilize additional sensors and the placement of the electrodes on the head or require a low SNR to achieve high performance [19].

This technical report focuses on the development of a voluntary eye blink classifier that utilizes only the signals recorded from the Ear EEG system in order to understand if this system provides sufficient information for signal classification. Chapter 2 details the experimental set up of the Ear EEG system and the recording of the voluntary eye blink trials that will be considered by the signals classifiers presented in later chapters. In order to set up a comprehensive classification framework that may be extended to more complex applications in future work, an assortment of spatial, temporal, and spectral features available to an in-ear system have been implemented and their effectiveness at classifying voluntary eye blink artifacts is compared. Additionally, four machine learning algorithms commonly used for classification of biological signals have been implement: logistic regression, support vector machine (SVM), random forest, and artificial neural networks. Often, the optimal choice of classifier model is application dependent and takes into consideration constraints such as the low SNR of EEG signals, whether or not an increased number of motion artifacts may be introduced due to the use of an ambulatory system, and subject to subject variability of EEG, which can make it difficult to obtain large training sets of data [20]. In Chapter 3 of this report, a logistic regression classifier, the simplest of these models, is implemented and feature analysis is discussed. Chapter 4 continues this analysis by discussing the implementations of a SVM, a random forest, and an artificial neural network models for eye blink classification and showing their respective results. This allows for the comparison of these algorithms for eye blink classification with this system and provides a basis for future work with more complex signal classification.

Chapter 2

Ear EEG Eye Blink Recordings

2.1 Ear EEG System

To collect voluntary eye blink data sets, a wireless, multielectrode, user-generic Ear EEG system is used for recordings [17] [18]. The Ear EEG system consists of a user-generic earpiece and a compact wireless neural recording module (WANDmini) that wirelessly transmits data to a base station at a sampling rate of 1000 samples per second (Fig 2.1a). A custom graphical user interface provides the subject with instructions and visual cues during the experiment and saves the recorded trials so they may be post-processed and examined for signal classification.

The user generic earpiece (Fig 2.1b) is designed with four in-ear electrodes, $E_1 - E_4$, positioned in the ear canal, and two out-of-ear electrodes, $E_5 - E_6$, that are positioned in the cymba and concha of the ear. Before recording trials with the Ear EEG system, an out-of-ear electrode, E_5 or E_6, is selected as a reference for each subject in order to maximize the differential EEG signal. The electrode-skin impedance (ESI) between these potential reference electrodes and the in-ear sense electrodes is recorded with an LCR meter, and an average ESI is calculated for each potential reference (Equation 2.1).

$$E_{ref}\ Average\ ESI = \frac{1}{4}\sum_{n=1}^{4} ESI\ ([E_n - E_{ref}]) \qquad (2.1)$$

The reference electrode with the lowest average ESI will be used during a subject's eye blink recordings (Fig 2.2).

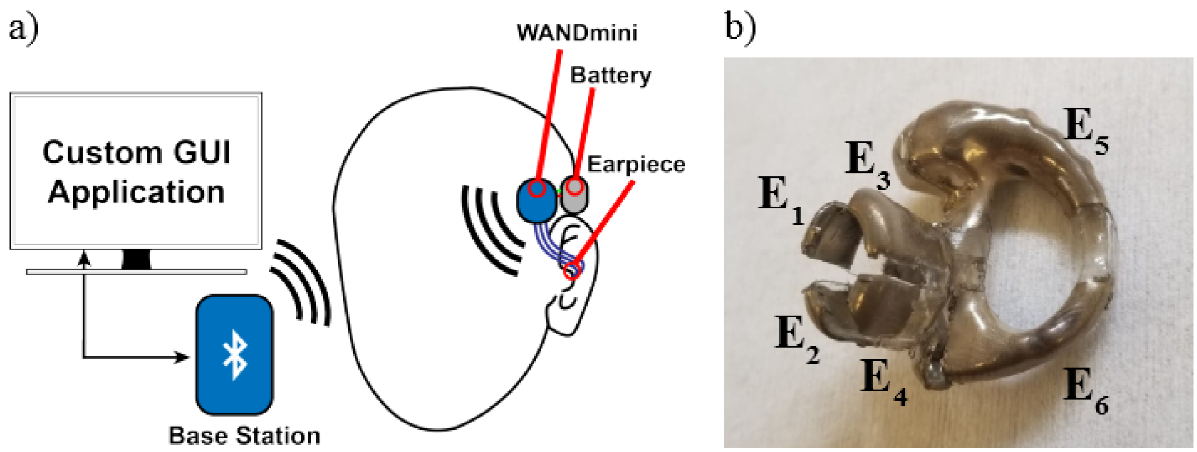

Fig. 2.1. (a) Experimental set up of Ear EEG system. (b) User-generic earpiece with labeled electrodes.

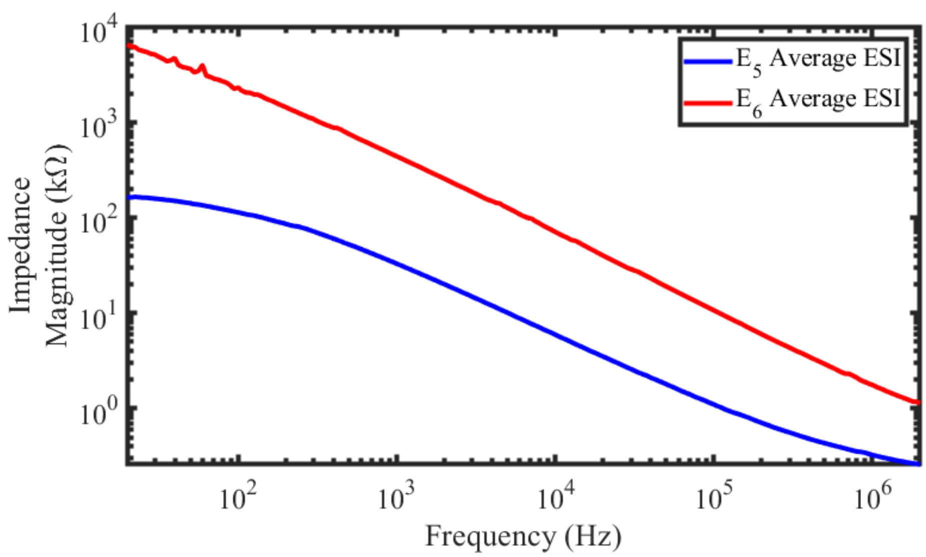

Fig. 2.2. Reference electrode selection for subject 2 based on LCR measurements. E_5 is selected as reference electrode for EEG recordings due to its lower average electrode-skin impedance magnitude (Equation 2.1).

2.2 Voluntary Eye Blink Recordings

Voluntary eye blinks were recorded across three subjects with the Ear EEG system providing a total of 100 trials that are each 50s in length (Table 2.1). The subject was asked to perform a hard eye blink when prompted by a visual cue from an on-screen GUI every 10s. The EEG signals recorded from the four in-ear electrodes are saved after each trial (Fig. 2.3).

Table 2.1
Number of Trials and Recorded Eye Blinks Per Subject

Subject	Number of Trials	Number of Eye Blinks Recorded
1	49	245
2	35	175
3	16	80

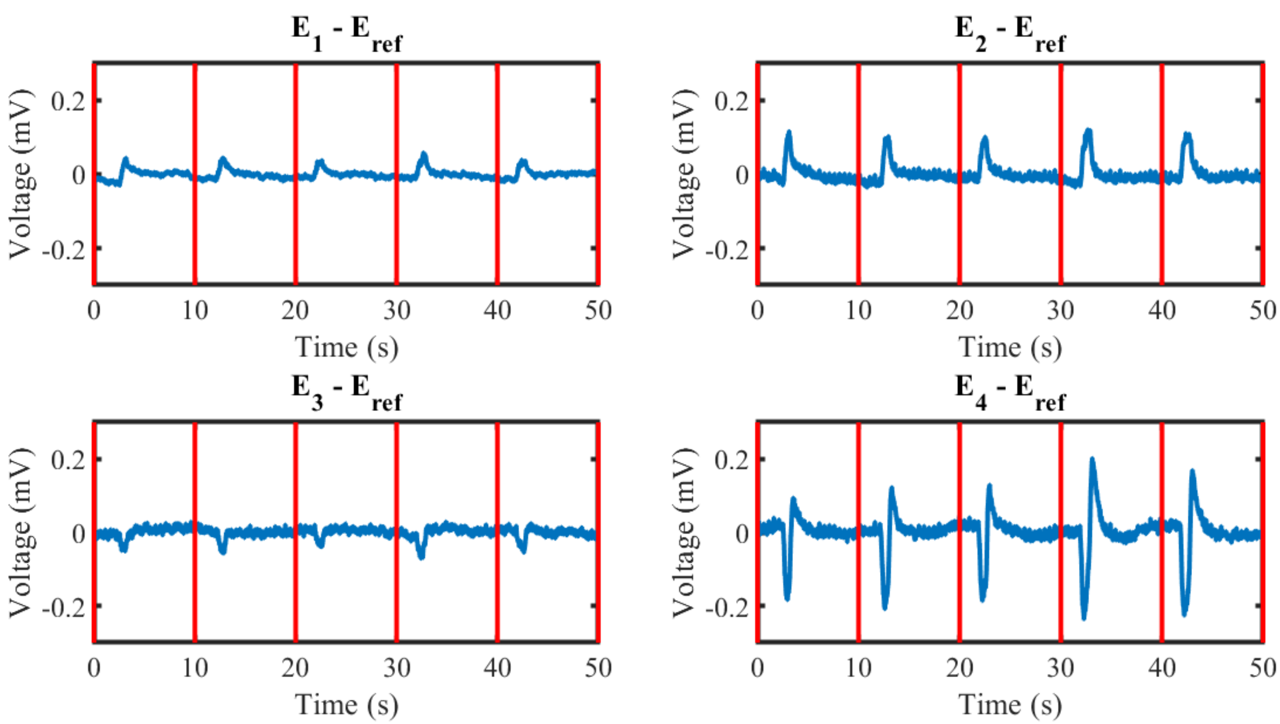

Fig. 2.3. Four in-ear EEG signals recorded during an eye blink trial (bandpass filtered from 0.05-50Hz). Red markers indicate eye blink cues given during the trial.

2.3 Eye Blink Labels

In order to train the signal classifiers and determine how effectively a classifier identifies the eye blinks, it is necessary to create eye blink event labels for each recorded trial. Eye blink labels are manually created by aggregating the four recorded EEG signals and visually identifying the voluntary eye blink following the cue provided to the subject during the trial (Fig. 2.4). A label is assigned to each sample of recorded data.

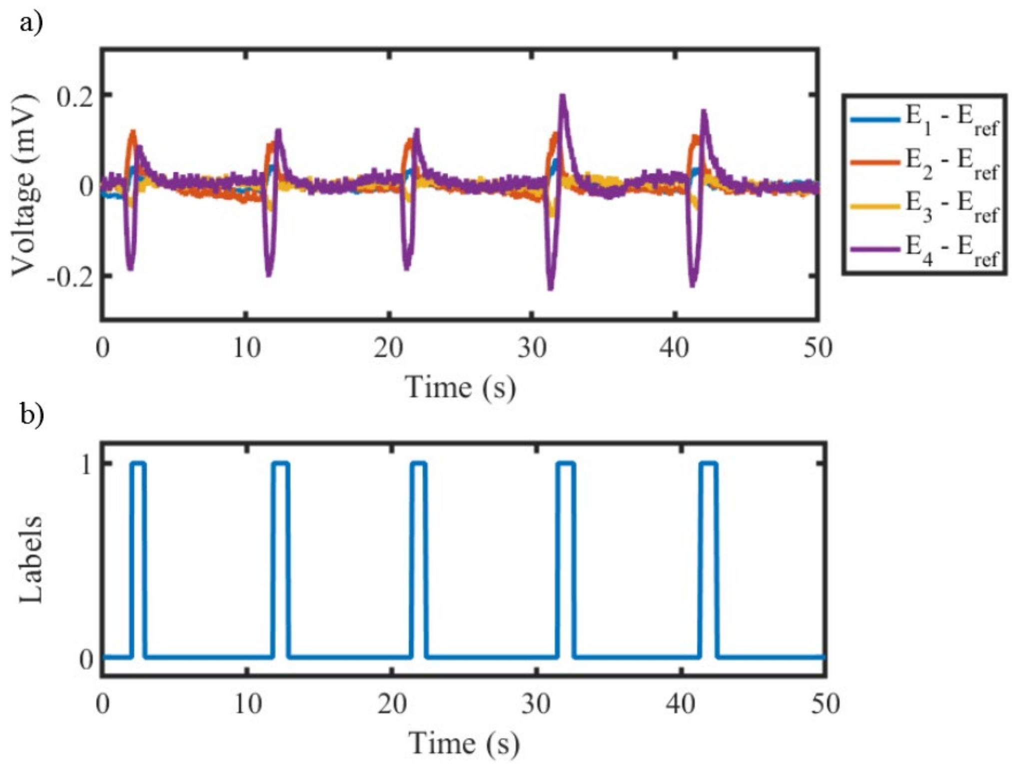

Fig. 2.4. Manually created labels for the four in-ear EEG signals recorded during the eye blink trial shown in Fig 2.3. (Eye blinks are bandpass filtered from 0.05-50Hz). '1' labels indicate eye blink samples.

Chapter 3

Eye Blink Classification: Logistic Regression Model

3.1 Logistic Regression Classification

The first eye blink classification algorithm considered in this report is implemented with a logistic regression classifier model. The logistic regression model considered here is binomial in that it is concerned with differentiating between '0' samples and '1' samples, which correspond to the rest and eye blink samples in the recorded eye blink trials. The labeling of these samples and the recording of eye blink trials was discussed in Chapter 2. This chapter focuses on the remaining components of an eye blink classification algorithm that can be represented as five blocks (Fig. 3.1). In order to achieve better separation of eye blink and rest samples using a classifier model, additional analysis of the recorded signals can be implemented prior to signal classification. This analysis, known as feature extraction, makes up block 3 and its implementation is discussed in Sections 3.3, 3.4, and 3.5. A final block is implemented after the classification of eye blink and rest samples to allow for the identification of eye blink events. This block is discussed in Section 3.2.

As shown in block 4 of Figure 3.1, a logistic regression classifier model can be represented generally by the sigmoid function in Equation 3.1, where $x_0 \ldots x_n$ represent the features passed to the classifier and $\beta_0 \ldots \beta_n$ represent feature weights the classifier trains to best model the '0' and '1' samples of a data set [21]. P represents the probability of a sample being in a '1' state, and a threshold of 0.5 is set in order to separate the instances of rest and eye blink events (Fig. 3.1, block 4).

$$P(1|x, \beta) = \frac{1}{1 + \exp\left(-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)\right)} \tag{3.1}$$

This classifier is implemented in python with the scikit logistic regression model. The model is trained on 50% of eye blink trials for a specific subject, and sample weights are provided to the classifier in order to account for the disbalance of rest and eye blink events in the data sets. The classifier is then tested on the remaining 50% of a subjects eye blink trials.

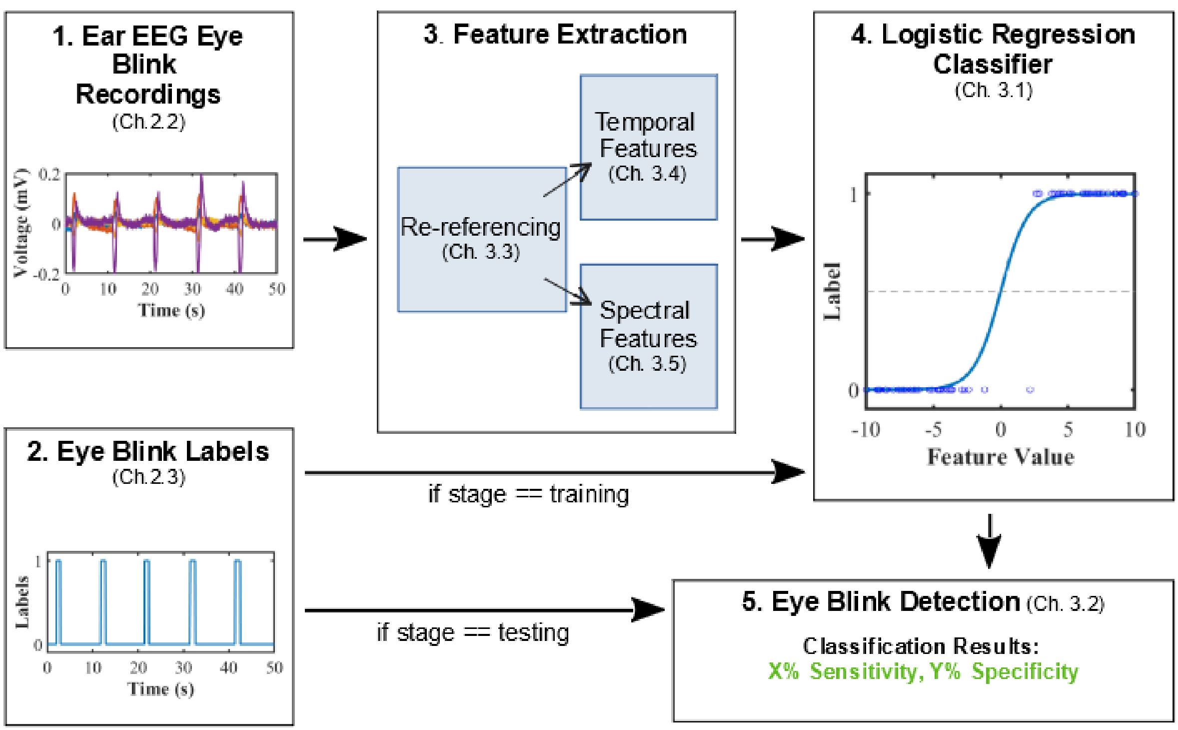

Fig. 3.1. Block diagram for eye blink classification with a logistic regression classifier.

3.2 Eye Blink Detection and Result Metrics

Classification results are commonly reported in terms of sensitivity and specificity metrics represented by Equations 3.2 and 3.3, which can be computed from a confusion matrix [20].

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{3.2}$$

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \tag{3.3}$$

In the context of eye blink classification, the confusion matrix can be defined in terms of eye blink events, since an eye blink event is more likely to be of significance to a BCI than the state of each individual sample of data (Table 3.1).

Table 3.1
Confusion Matrix for Eye Blink Classification

Term	Description
True Positive	Classifier correctly detects an eye blink event
False Negative	Classifier fails to detect an eye blink event
True Negative	Classifier correctly detects a rest event
False Positive	Classifier falsely detects an eye blink event

In order to identify eye blink events and report the sensitivity and specificity for this eye blink classification algorithm, block 5 of Figure 3.1 acts as an eye blink detector that can be represented visually as a finite state machine (Fig. 3.2). The purpose of this state machine is to translate classification results for each sample of data into classification results for eye blink events. During training, this block sets a window size equivalent to the maximum duration of a subject’s eye blinks, approximately 1.5s (Fig. 3.3), and a threshold for eye blink detection equivalent to the minimum duration of a subject's eye blinks, approximately 0.3s. During testing, decisions about whether or not an event has occurred are reported every 1s. If the number of samples identified as eye blinks in a window exceeds the preset threshold, it is verified that an eye blink was not detected in the previous detector window. If two eye blinks are identified consecutively, the overlap between these windows is checked for samples labeled as eye blinks, and the second eye blink event is reported only if this overlapping region is free of eye blink samples. This logic prevents the eye blink detector from reporting a single eye blink event twice. Once eye blink events and rest events have been identified in the classifier's predicted labels and the manually created labels, these results are compared to report the classifier's sensitivity and specificity.

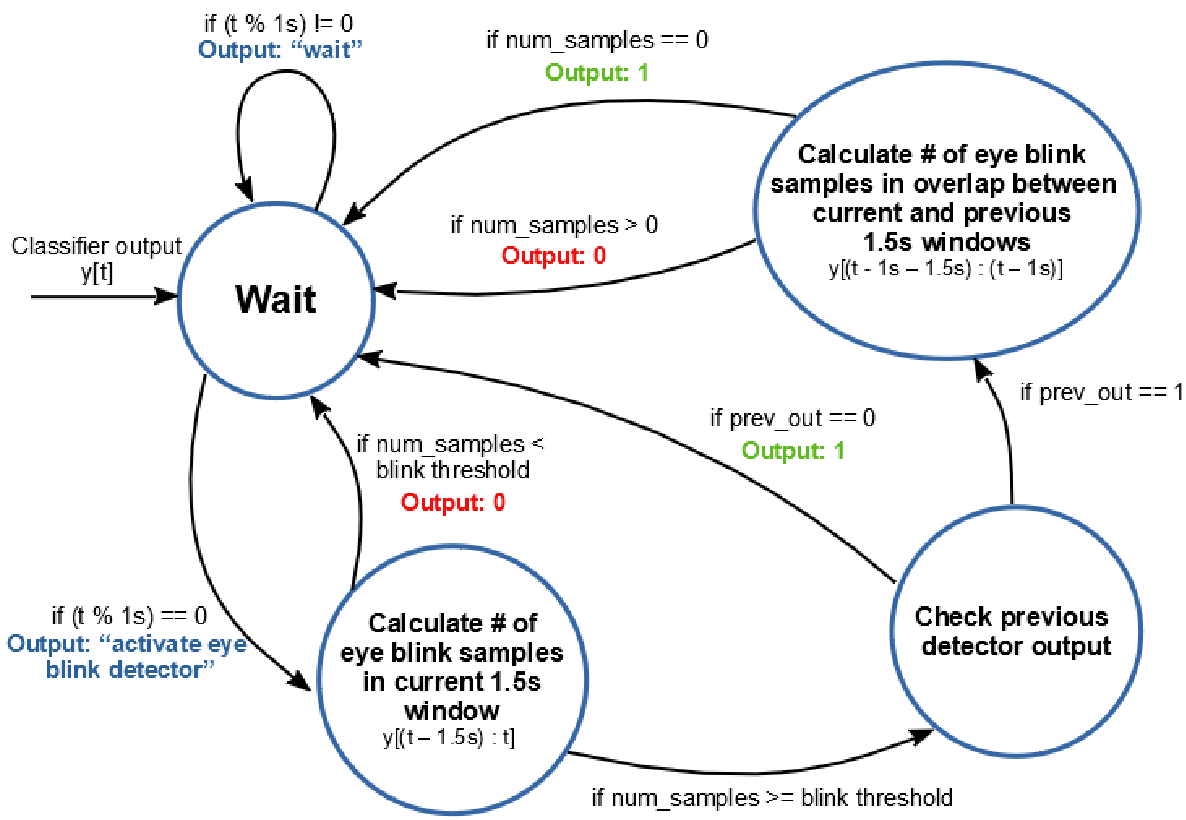

Fig. 3.2. Finite State Machine for eye blink event detection during testing. A detector output of '1' indicates an eye blink event. A detector output of '0' indicates a rest event.

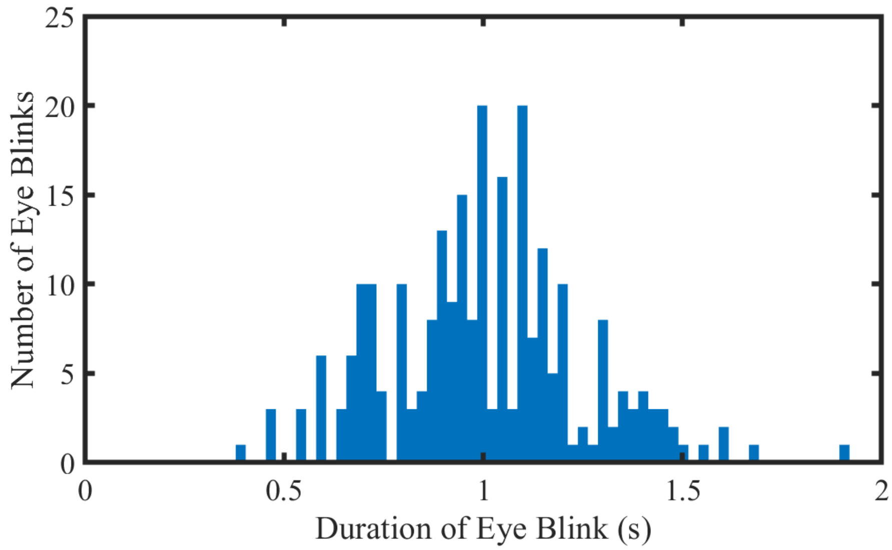

Fig. 3.3. Eye blink durations (widths) for subject 1 calculated according to manually created data labels.

3.3 Feature Extraction: Re-referencing

A common method used to identify eye blink artifacts in an EEG datasets is to consider the location of the electrodes on the head as features that may be passed to a signal classifier. In the clinical setting, it may be practical to rely on electrodes positioned around the eye, EOG, to provide information about when an eye blink artifact has occurred [19]. Additionally, the frontal electrodes of scalp EEG systems record greater amplitude eye blink artifacts then scalp EEG electrodes in other locations allowing for eye blink signal classifiers to take advantage of this signal variation [22]. These are considered spatial features for EEG signal classification.

A fundamental challenge of EEG signal classification from within the ear is the close-proximity of the in-ear electrodes, which make it difficult to take advantage of spatial features for the purpose of greater signal variation. However, signal re-referencing can be implemented as a spatial feature in the context of in-ear EEG in order to reduce the impact of motion artifacts due to the movement of the user-generic earpiece. Recall from section 2.1, an out-of-ear electrode, E_5 or E_6, is selected as a reference electrode for a subject's EEG recordings (Fig. 2.2). Though these out-of-ear electrodes provide the largest differential signal, they tend to be the more mechanically unstable than the in-ear electrodes that are held in place by the ear canal. When a subject performs a voluntary eye blink, the movement of the facial muscles can cause a change in the electrode-skin impedance of the out-of-ear reference electrode and introduce artifacts in the recorded data (Fig. 3.4a, Fig 3.4b). This effect tends to occur more frequently in specific subjects due to the fit of the user-generic earpiece.

Since measurements with all in-ear electrodes are recorded with the same out-of-ear reference electrode, a new differential signal can be calculated by re-referencing each signal as shown in Equation 3.4. This technique removes the mechanical artifacts caused by the out-of-ear reference (Fig 3.4c).

$$[E_{sense\ 1} - E_{ref}] - [E_{sense\ 2} - E_{ref}] = [E_{sense\ 1} - E_{sense\ 2}] \qquad (3.4)$$

In order ensure the eye blink classifier is provided features without these mechanical instabilities, each dataset is expanded to include a combination of the recorded EEG signals and the in-ear re-referenced signals (Table 3.2), and all further feature extraction is performed on this expanded data set. In the case of subject 3, the eye blink classification results with the recorded signals are only 85.2% sensitivity and 98.3% specificity when all features discussed in this chapter are implemented; however, when recorded and re-referenced signals are considered these results increase to 97.1% sensitivity and 100% specificity. This demonstrates the significance of re-referencing for eye blink classification with the Ear EEG system.

Table 3.2
Electrode Differential Pairs Considered During Eye Blink Classification

Recorded EEG Signals	Re-referenced EEG Signals
$E_1 - E_{ref}$	$E_1 - E_2$
$E_2 - E_{ref}$	$E_1 - E_3$
$E_3 - E_{ref}$	$E_1 - E_4$
$E_4 - E_{ref}$	$E_2 - E_3$
	$E_2 - E_4$
	$E_3 - E_4$

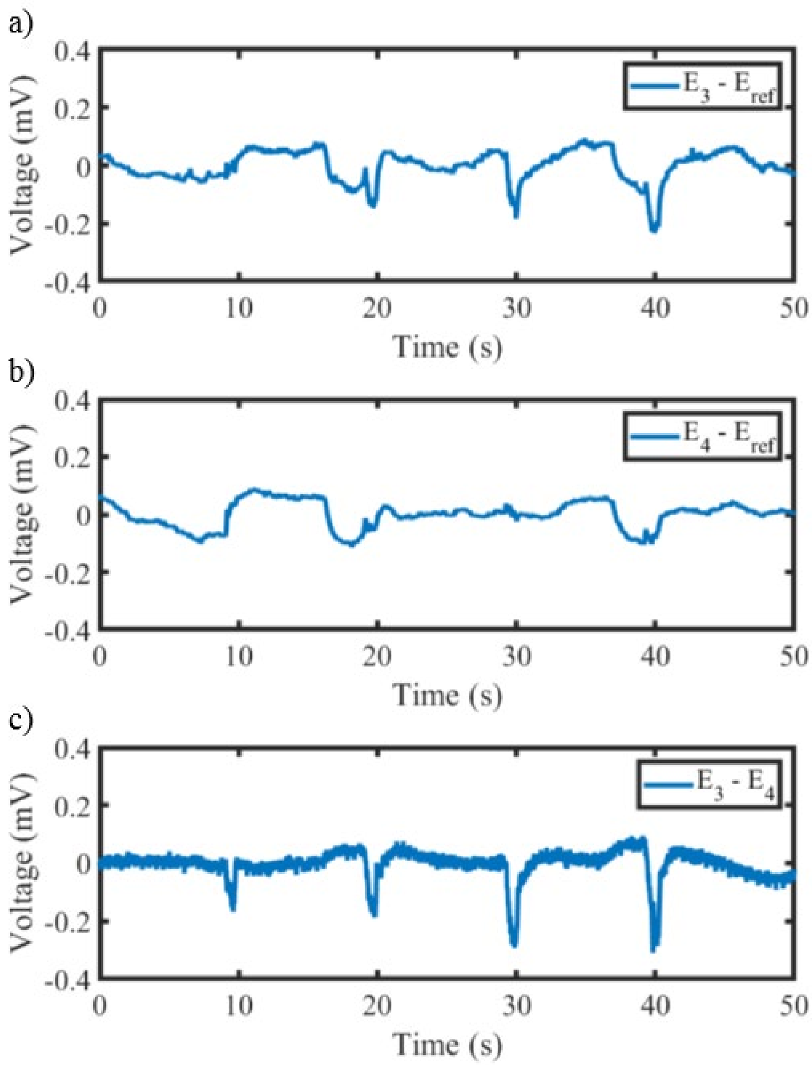

Fig. 3.4. (a), (b) Recorded eye blinks with mechanical artifacts due to movement of out-of-ear reference electrode. (c) Re-referenced eye blinks with mechanical artifacts removed.

3.4 Feature Extraction: Temporal Features

Four time-domain features (temporal features) are calculated for each of the recorded EEG and re-referenced EEG signals. In the following subsections, these feature calculation are introduced, and the sensitivity and specificity of eye blink classification with a logistic regression model that uses the indicated feature is shown per subject. This allows for a numerical comparison of the effectiveness of the signal classifier based on which features are implemented.

3.4.1 Voltage Amplitude Feature

Eye blink events are characterized by an abrupt change in voltage amplitude [22]. In order to make this change in amplitude more apparent in the signal, each of the recorded EEG signal and re-referenced EEG signal is bandpass filtered form 0.05Hz - 10Hz, and the resulting signals are used as features for eye blink classification (Fig. 3.5). This feature calculation relies on the consistency of the voltage amplitude across eye blink events for a specific subject, which may be effected by the electrode skin impedance and variability in how the subject performs an eye blink.

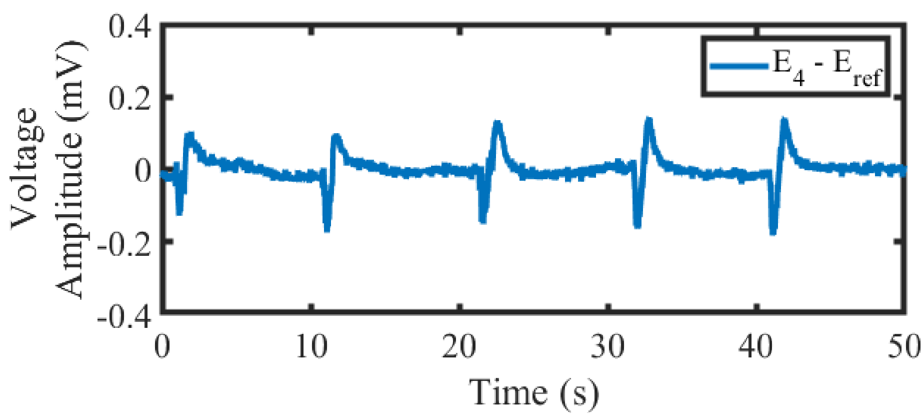

Fig. 3.5. Voltage amplitude feature calculated for one recorded signal of EEG data.

Table 3.3

Logistic Regression Classification with Voltage Amplitude Features

Subject	Sensitivity	Specificity
1	83.9 %	98.8 %
2	84.8 %	96.9 %
3	90.6 %	97.4 %

3.4.2 Derivative Feature

In order to take advantage of the abrupt change in voltage amplitude that is characteristic of eye blink artifacts, derivative-based features have been used to identify eye blinks in frontal EEG electrodes and EOG recordings [19] [23]. In this report, a simple derivative feature is implemented according to Equation 3.5, where y(x) indicates the bandpass filtered voltage amplitude of the sample located at time, x. The parameter Δx is set to 0.05s in order to calculate the slope of the y-axis slope through point x. The absolute value of this derivative is taken, in order to avoid a sign difference in the feature values corresponding to the rising and falling edges of an eye blink (Fig. 3.6).

$$D(x) = abs\left(\frac{y(x+\Delta \mathrm{x}) - y(x-\Delta \mathrm{x})}{(x+\Delta \mathrm{x}) - (x-\Delta \mathrm{x})}\right) \tag{3.5}$$

This feature identifies eye blink events based on the sharp changes in voltage amplitude that is characteristic of all eye blink artifact, which results in very high sensitivity across all subjects (Table 3.4). However, the specificity of the eye blink classifier is low when this feature is implemented due to inability to separate motion artifacts in the data sets from eye blink events.

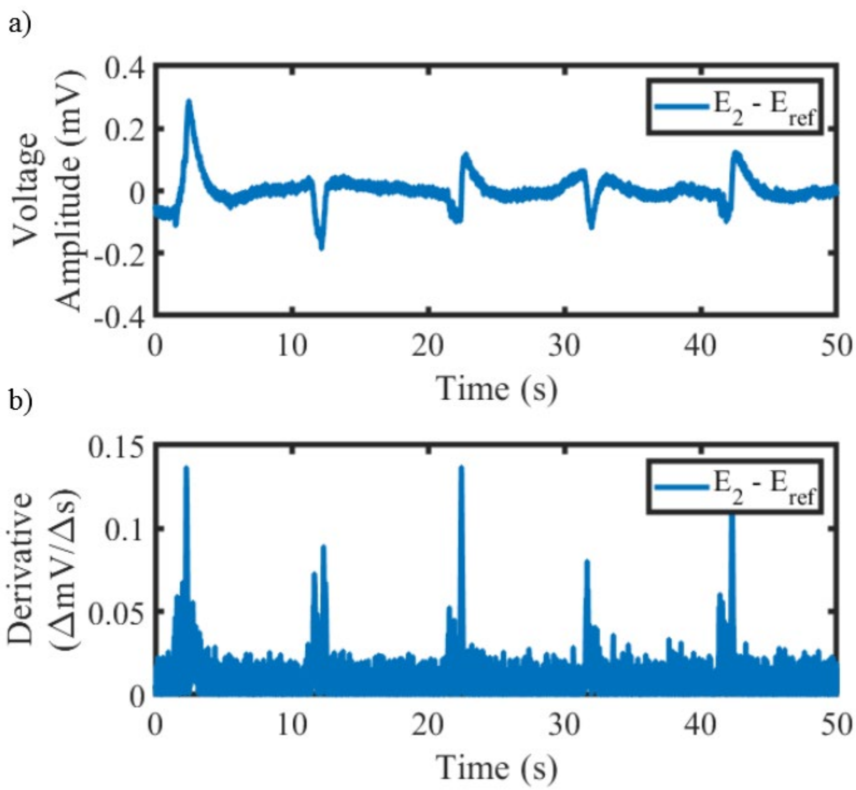

Fig. 3.6. Comparison of (a) voltage amplitude feature to (b) derivative feature for same recorded signal of EEG data.

Table 3.4
Logistic Regression Classification with Derivative Features

Subject	Sensitivity	Specificity
1	98.0 %	92.3 %
2	100 %	89.9 %
3	100 %	91.0 %

3.4.3 Standard Deviation Feature

Eye blink artifacts are characterized by an increase in the standard deviation of the EEG voltage amplitude [24]. In order to compute a standard deviation feature, a sliding window is implemented, and the standard deviation of the bandpass filtered voltage amplitude is computed and assigned as the feature value for the center-most sample of this sliding window (Fig. 3.7). To select an optimum length for this sliding window, the window length parameter is trained to maximize the sensitivity of eye blink classification while specificity remains above 95%. The optimal sliding window length for all subjects is between 0.4s and 0.5s.

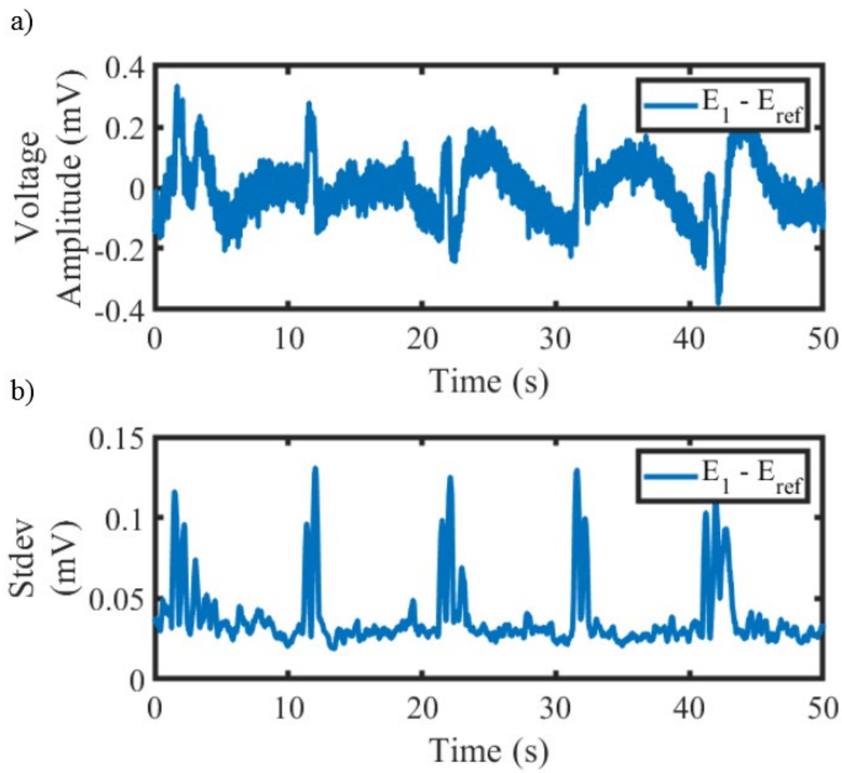

Fig. 3.7. Comparison of (a) voltage amplitude feature to (b) standard deviation feature for same recorded signal of EEG data.

Table 3.5

Logistic Regression Classification with Standard Deviation Features

Subject	Sensitivity	Specificity
1	73.2 %	99.7 %
2	100 %	98.3 %
3	93.8 %	93.8 %

3.4.4 Standard Deviation Ratio Feature

In order to better separate eye blink events from motion artifacts in the EEG signal, a variation of the standard deviation feature is implemented where a ratio is calculated between the standard deviation of two sliding windows according to Equation 3.6 (Fig. 3.8). The delay length between the two sliding windows is set such that the total time elapsed from the start of the current window to the end of the delayed window is 1.5s, roughly the maximum duration of eye blinks recorded with this system (Fig 3.3).

$$Ratio\ (x) = \frac{stdev(current\ window)}{stdev(delayed\ window)} \tag{3.6}$$

The sensitivity and specificity of eye blink classification with this ratio feature increases compared to the previous standard deviation feature across all subjects due to the suppression of motion related artifacts in the signal as these ratios are computed.

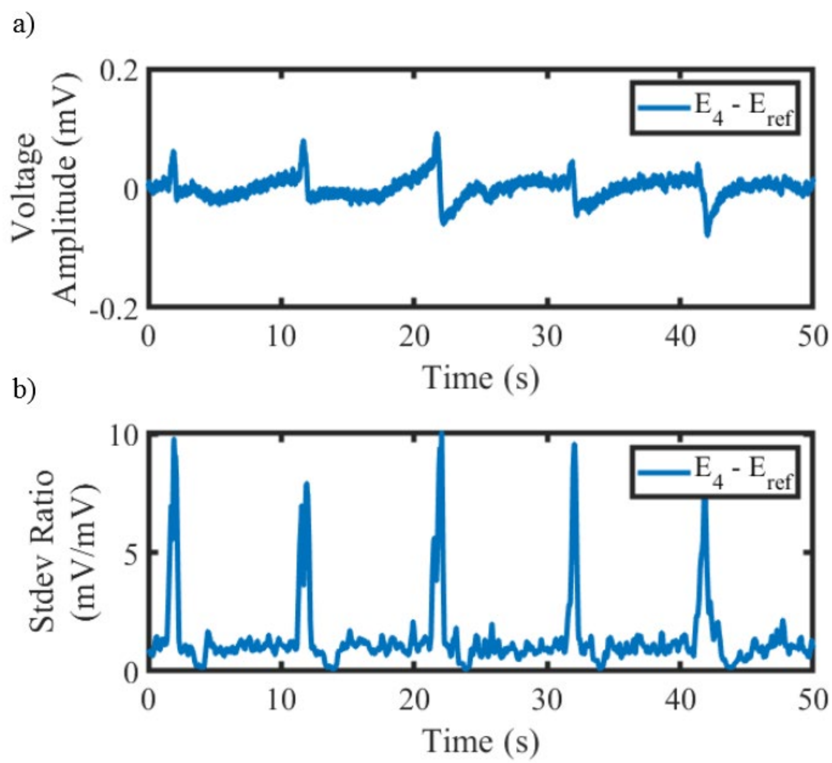

Fig. 3.8. Comparison of (a) voltage amplitude feature to (b) standard deviation ratio feature for same recorded signal of EEG data.

Table 3.6

Logistic Regression Classification with Standard Deviation Ratio Features

Subject	Sensitivity	Specificity
1	100 %	99.6 %
2	100 %	98.1 %
3	96.8 %	98.9 %

3.5 Feature Extraction: Spectral Features

EEG signals are often analyzed in terms of frequency bands: Delta (δ) 0.05 - 4 Hz, theta (θ) 4 - 7 Hz, alpha (α) 8 – 12 Hz, beta (β) 12 - 30 Hz, and gamma (γ) 30 - 50 Hz. The band power and peak power spectral density (PSD) of these frequency ranges commonly appear as features in EEG drowsiness classifiers, and eye blink movement is often visible in the delta band, δ (0.05 - 4 Hz) [8] [19]. This is demonstrated in Figure 3.9. In the following subsections, three power spectral features are implemented in the delta band to classify eye blink events. For each feature, the power spectral density of a 2s sliding window is computed using the Welch method with a Hanning window and 50% overlap [25]. The features are then calculated based on the power spectral density of the 2s window surrounding the given sample.

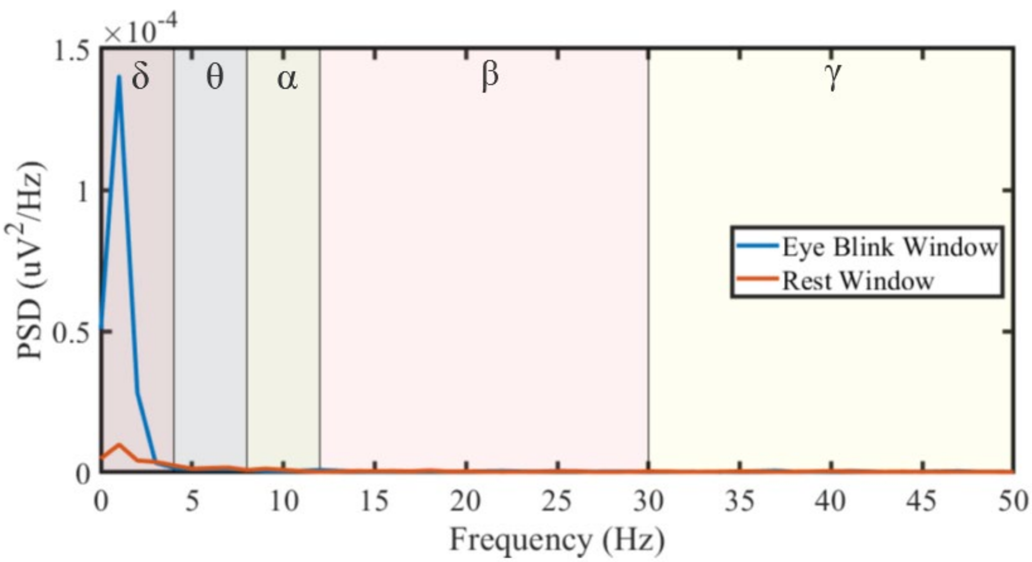

Fig. 3.9. PSD of EEG signal for a 2s eye blink window and a 2s rest window. EEG frequency bands are labelled. Increased PSD in delta band during an eye blink window is demonstrated.

3.5.1 Peak PSD in Delta Band Feature

The peak of the power spectral density in the delta band is calculated by determining the maximum PSD between 0.5 and 4Hz in 2s window of data surrounding a given sample (Fig. 3.10). The high sensitivities and specificities across all subjects (Table 3.7) indicate a strong correlation between an increase in peak power spectral density in the delta band during a voluntary eye blink, as was observed in Figure 3.9.

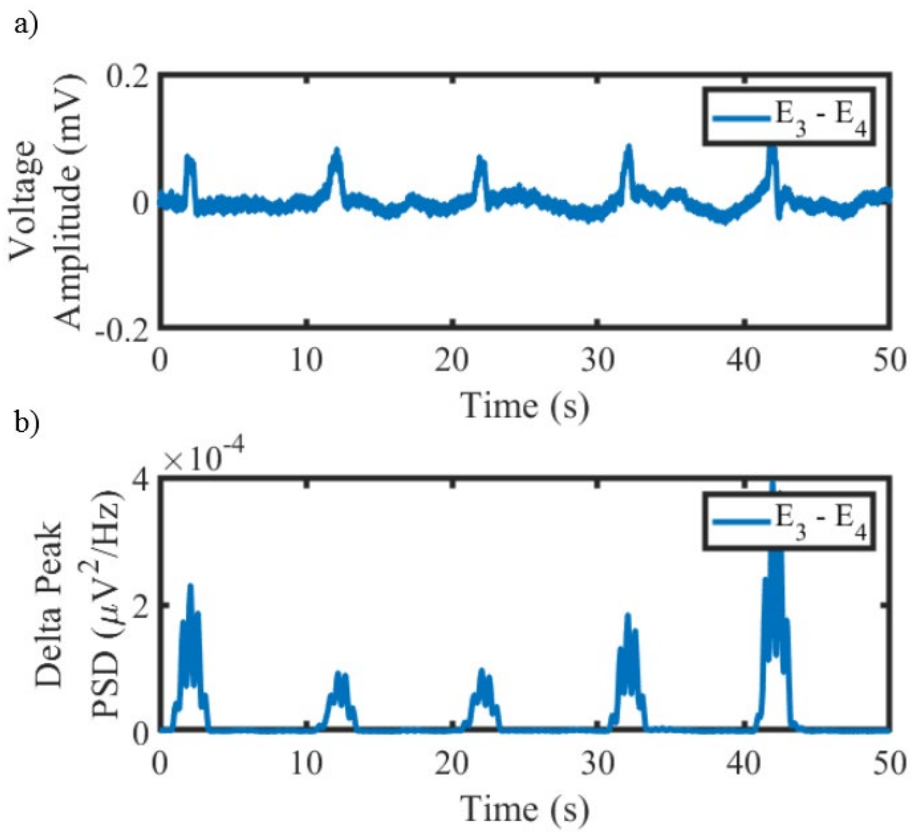

Fig. 3.10. Comparison of (a) voltage amplitude feature to (b) peak PSD in delta band feature for same re-referenced signal of EEG data.

Table 3.7
Logistic Regression Classification with Peak PSD in Delta Band Features

Subject	Sensitivity	Specificity
1	95.1 %	99.0 %
2	100 %	99.6 %
3	100 %	100 %

3.5.2 Absolute Delta Band Power Feature

The absolute delta band power of a 2s window of the EEG signal can be computed by estimating the area under the PSD curve in the delta band using Simpson's rule (Fig. 3.11). There is a decrease in specificity with this feature in comparison to the peak PSD feature in the previous subsection (Table 3.8). This is the result of the absolute band power feature identifying spontaneous eye blinks as false positives, which may also interfere with the classifiers ability to train itself to separate the eye blink and rest events in these EEG signals and explain the decrease classification sensitivity. While this feature is not as effective for voluntary eye blink classification in these data sets as the peak delta PSD feature, it may be more effective for applications where spontaneous eye blinks are targeted by a signal classifier. This is often the case in drowsiness detection, where absolute band power in the delta band is a commonly implemented feature [19].

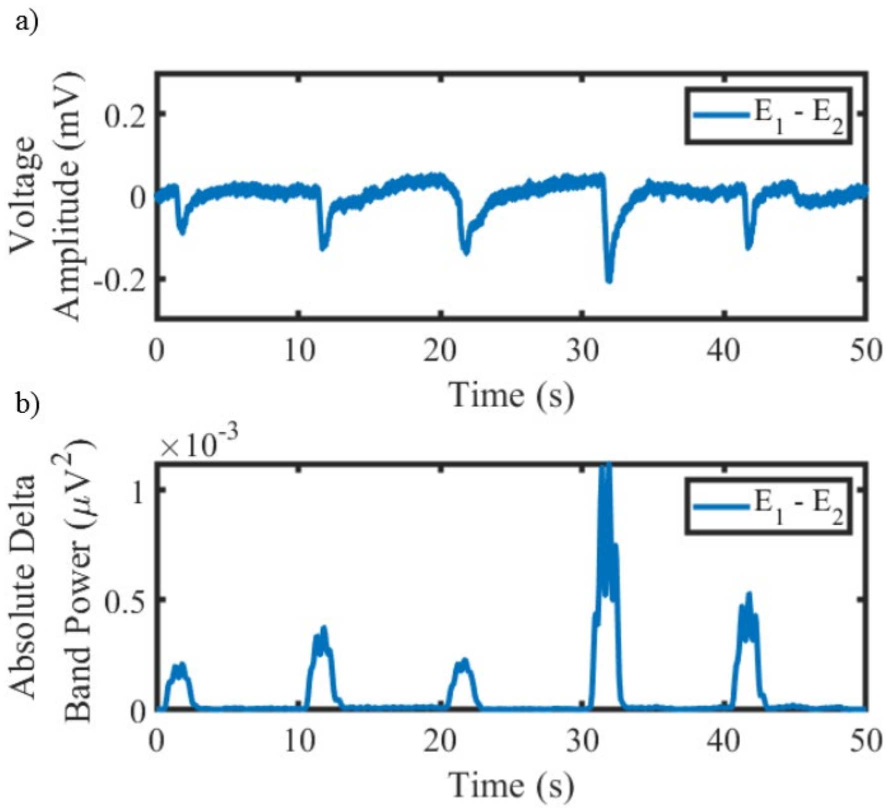

Fig. 3.11. Comparison of (a) voltage amplitude feature to (b) absolute delta band power feature for same re-referenced signal of EEG data.

Table 3.8
Logistic Regression Classification with Absolute Delta Band Power Features

Subject	Sensitivity	Specificity
1	92.3 %	96.0 %
2	100 %	99.4 %
3	100 %	97.1 %

3.5.3 Relative Delta Band Power Feature

The relative delta band power of a 2s window of the EEG signal can be computed by estimating the area under the PSD curve in the delta band using Simpson's rule and dividing it by the area under the PSD curve in the 0.05 - 50Hz frequency range. This calculation results in the percentage of the total of the EEG band power made up of delta band power (Fig. 3.12). This feature may be less optimal for eye blink classification due to its dependence on the EEG activity in other frequency bands, which may be inconsistent from trial to trial. Similar to the absolute delta band power feature, this feature has a lower specificity due to spontaneous eye blinks appearing as false positives (Table 3.9).

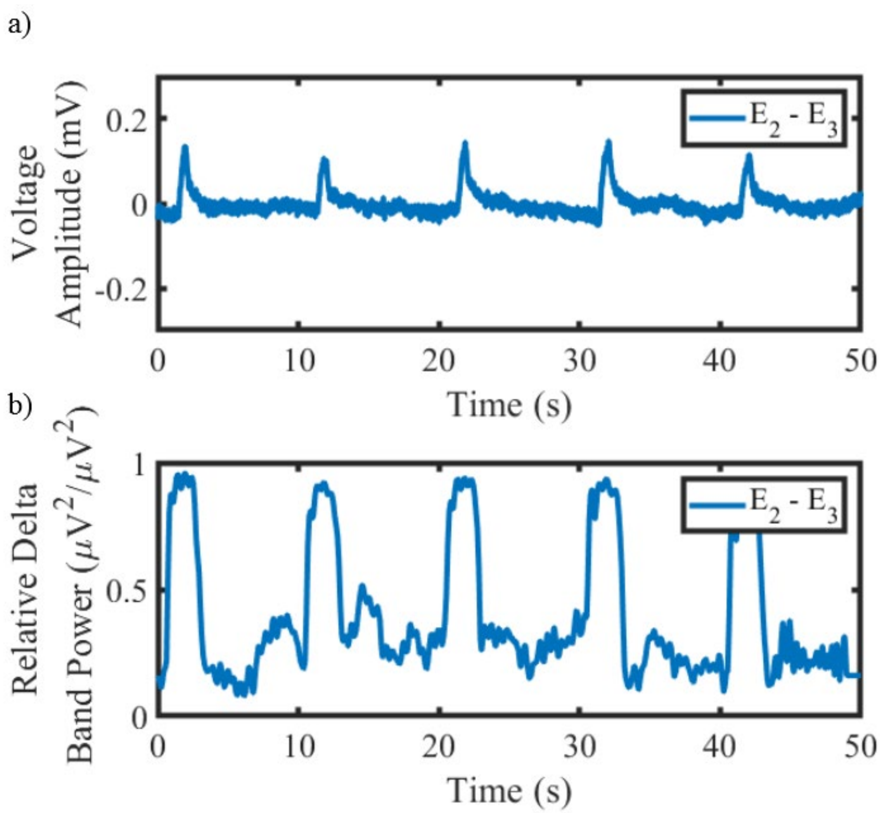

Fig. 3.12. Comparison of (a) voltage amplitude feature to (b) relative delta band power feature for same re-referenced signal of EEG data.

Table 3.9
Logistic Regression Classification with Relative Delta Band Power Features

Subject	Sensitivity	Specificity
1	88.7 %	99.5 %
2	99.0 %	99.3 %
3	96.9 %	97.8 %

3.6 Summary

To conclude the analysis of eye blink classification using the logistic regression model, the weighted average of the sensitivity and specificity of eye blink classification for each subject is calculated for each of the features analyzed in this chapter. These averages are calculated according to Equations 3.7 and 3.8, which takes into consideration the number of trials per subject in order account for the varying numbers of eye blinks across subjects.

$$Average\ Sensitivity = \sum_{n=1}^{3} [sensitivity_{subject\ n}] * \left[\frac{number\ of\ trials_{subject\ n}}{number\ of\ trials_{all\ subjects}}\right] \quad (3.7)$$

$$Average\ Specificity = \sum_{n=1}^{3} [specificity_{subject\ n}] * \left[\frac{number\ of\ trials_{subject\ n}}{number\ of\ trials_{all\ subjects}}\right] \quad (3.8)$$

In addition to the analysis presented in sections 3.4 and 3.5 where a single feature calculation occurs in the feature extraction block, an overall analysis was completed in which all seven features presented in this chapter are calculated for the recorded and re-referenced EEG signals during the feature extraction block. This allows the classifier model to consider multiple features as indicators of eye blink and rest events and train optimal feature weights for a particular subject. These features are normalized by removing the median and scaling the data according to the quantile range in order to ensure their y-axis scales are comparable before feature weights are assigned. The results of this analysis are presented in Figure 3.13.

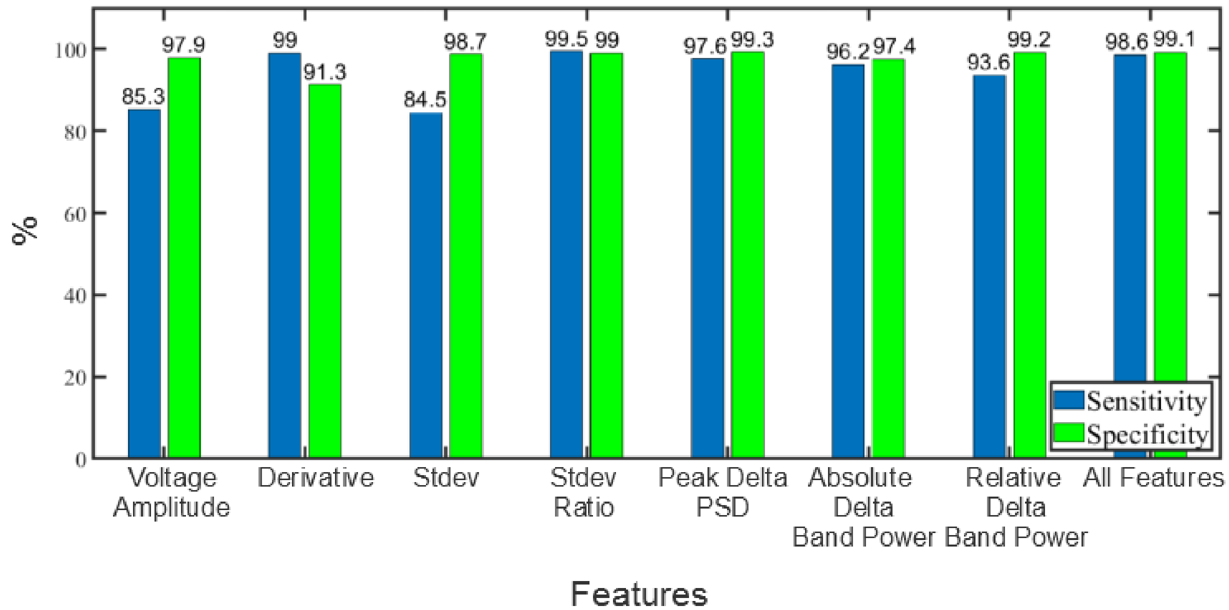

Fig. 3.13. Average sensitivity and specificity (Equation 3.7, 3.8) for eye blink classification with logistic regression classifier when implemented with features indicated on the x-axis.

From this analysis, we conclude that eye blinks may be detected with 98.6% sensitivity and 99.1% specificity when the features detailed in this chapter are implemented simultaneously with a logistic regression classifier model. The results of eye blink classification with individual feature calculations allows for future work to select which features may be best suited for a specific BCI application with an understanding of their eye blink classification results.

Chapter 4

Eye Blink Classification: Classifier Model Comparisons

4.1 Support Vector Machine Classification

In order continue the analysis of eye blink classification with the Ear EEG system, three additional classifier models are implemented to compare their classification results to those of the logistic regression model presented in Chapter 3. In this section, a support vector machine (SVM) is implemented (Fig. 4.1).

A SVM is a classifier that constructs an optimum decision boundary, called a hyperplane, between the states the classifier is concerned with separating. For eye blink classification, these states are '0' for rest events, and '1' for eye blink events. Here, an SVM with a linear kernel is used to create an optimal decision boundary that is defined as the maximum margin that can be created between the decision boundary and the data samples being classified [4] [21]. The number of features provided to the classifier, n, will be separated by a decision boundary of dimension n - 1. For a 2-dimensional problem where only two features are considered by the SVM, this can be visualized as a scatter plot where the x and y axes represent feature values, and a line with maximum distance between the two classes is drawn between the data samples (Fig. 4.1, block 4).

This classifier is implemented in python with the scikit linear SVC model. Similar to the logistic regression classifier previously used, the model is trained on 50% of the eye blink trials for a specific subject, and sample weights are provided to the classifier in order to account for the imbalance of rest and eye blink events in the data sets. The classifier is then tested on the remaining 50% of a subjects eye blink trials.

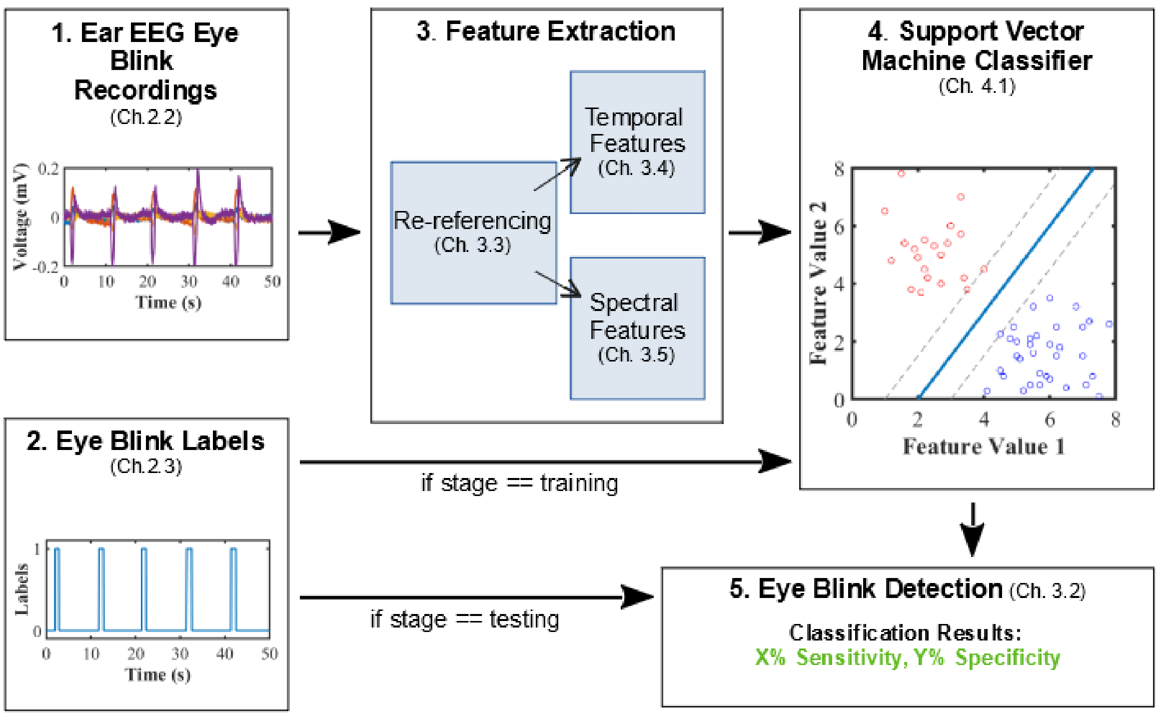

Fig. 4.1. Block diagram for eye blink classification with a SVM classifier.

In order to create a fair comparison between these classifier models, the same feature extraction steps and analysis from Chapter 3 are repeated. The average sensitivity and specificity of the three subjects results are reported below (Fig. 4.2).

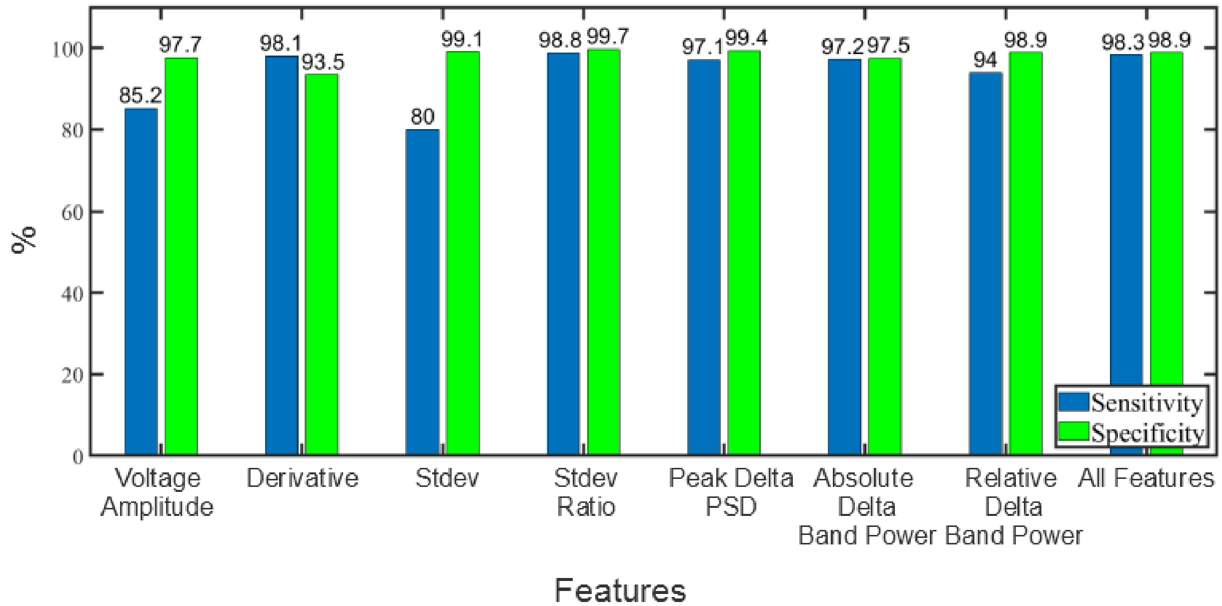

Fig. 4.2. Average sensitivity and specificity (Equation 3.7, 3.8) for eye blink classification with SVM classifier when implemented with features indicated on the x-axis.

From this analysis, we conclude that eye blinks may be detected with 98.3% sensitivity and 98.9% specificity when the features detailed in Chapter 3 are implemented simultaneously with the SVM classifier model. This is a 0.3% decrease in sensitivity and a 0.3% increase in specificity compared to the logistic regression classifier implemented with the same features in Chapter 3. These results are consistent with expectations, as the high sensitivity and specificity achieved using a logistic regression classifier indicated the eye blinks events and rest events in the EEG signals are linearly separable. An SVM may be implemented with a kernel trick to create a non-linear decision boundary, which may reduce the few outlying cases present in this data set. However, these methods are computationally more complex, and may lead to overfitting the data.

4.2 Random Forest Classification

The third eye blink classification algorithm is implemented with a random forest classifier model. Random forest classifiers are often utilized in BCI due their ability to achieve high classification accuracy with small sets of training data [20]. A random forest classifier works by constructing an ensemble of decision trees based on random subsets of the features available to the classifier (Fig. 4.3, block 4). A final decision about the state of a sample is then made by aggregating the results of these decision trees [20].

The random forest classifier in this report is implemented in python with the scikit random forest classifier. A maximum tree depth is set to 3 in order to reduce the classifier complexity and the memory it requires. Similar to the logistic regression and SVM classifiers, the model is trained with 50% of a subjects eye blink trials and tested on the remaining 50% of their trials. Sample weights are provided to the classifier in order to account for the imbalance of rest and eye blink events in the data sets.

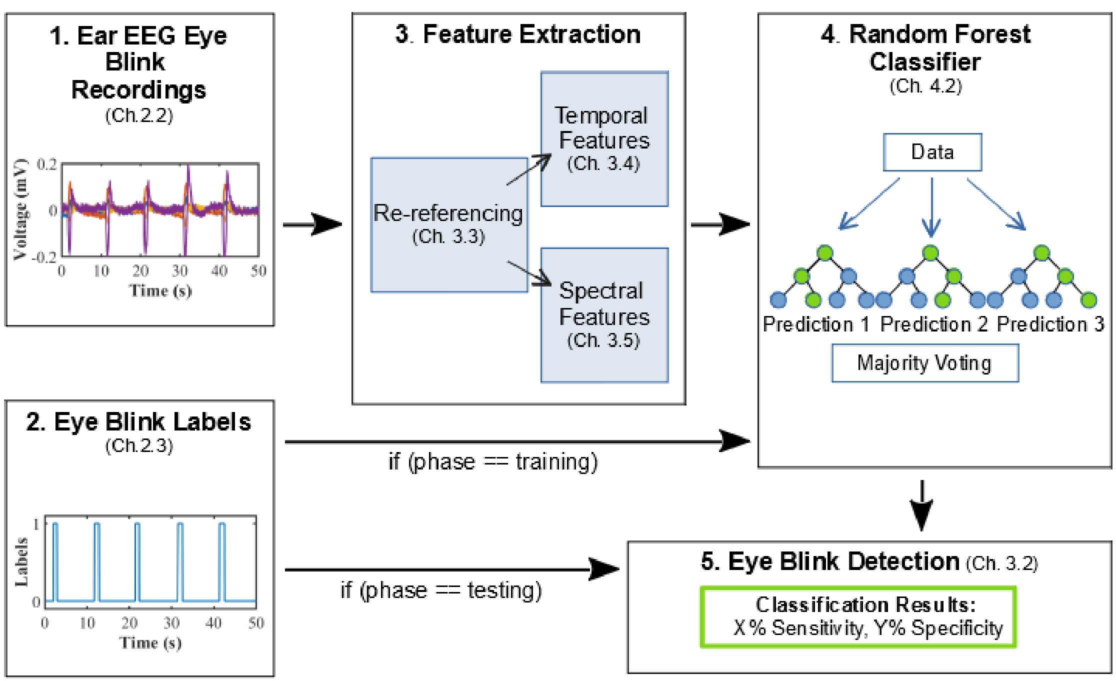

Fig. 4.3. Block diagram for eye blink classification with a random forest classifier.

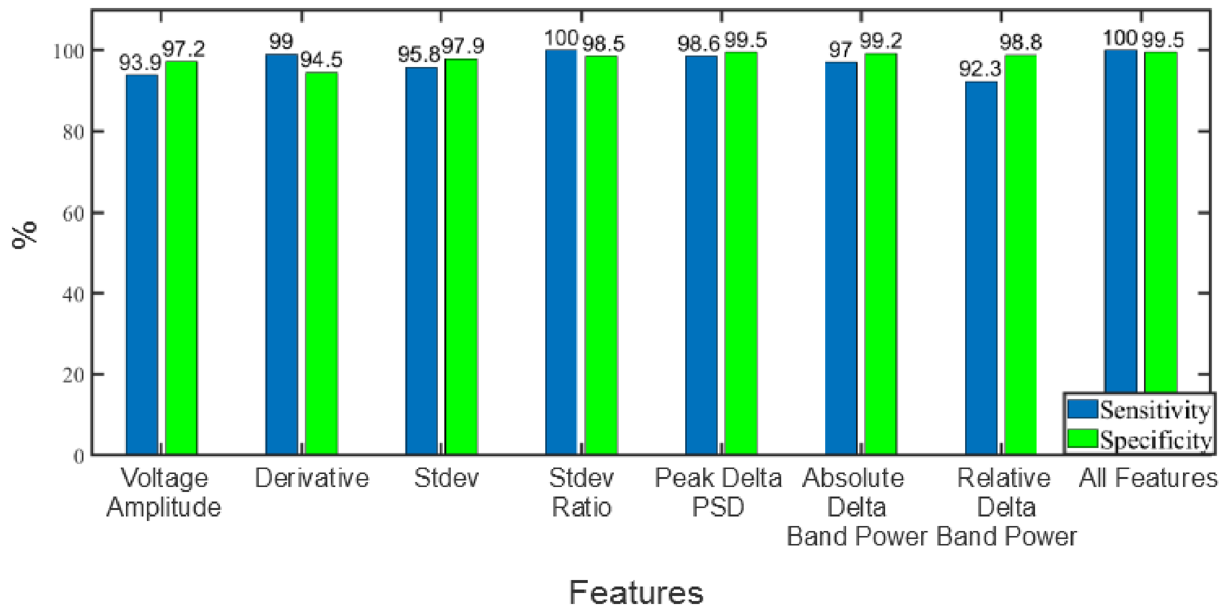

Fig. 4.4. Average sensitivity and specificity (Equation 3.7, 3.8) for eye blink classification with random forest classifier when implemented with features indicated on the x-axis.

From this analysis, we conclude that eye blinks may be detected with 100% sensitivity and 99.5% specificity when the features detailed in Chapter 3 are implemented simultaneously with the random forest classifier. Generally, sensitivity and specificity increased with a random forest classifier in comparison to the results from a logistic regression or SVM classifier implemented with the same features. This makes random forest an ideal classifier model to consider for future work with Ear EEG classification.

4.3 Artificial Neural Network Classification

The final classifier implemented in this report is an artificial neural network. A neural network is a black-box machine learning algorithm, in which hidden layers approximate a non-linear decision boundary between the desired classification states by learning mathematical relationships between the inputs and desired outputs of the classifier and adjusting the internal weights of 'neurons' to classify a data set [20] [26]. Neural networks are often capable of achieving high classification accuracy without the more complex feature extraction blocks required for logistic regression, SVM, and random forest classifier models. However, neural networks require high computational power, and often large training data sets in order to achieve high sensitivity and specificity, which may make them not ideal for an embedded system or BCI [26].

The neural network in this report is implemented in python with the TensorFlow sequential model. Two hidden layers are implemented with a ReLU activation function and a binary cross entropy loss function. The model is trained with 50% of eye blink trials for a specific subject, and sample weights are provided to the classifier in order to account for an unbalanced number of eye blink and rest events in the data sets. The model is tested on the remaining 50% of a subjects eye blink trials. The block diagram for the neural network eye blink classification algorithm differs from the logistic regression, SVM, and random forest diagrams in that the more complex feature extraction block from previous block diagrams has been replaced by a simpler feature extraction block (Fig. 4.5). In this case, the feature extraction block re-references the EEG signals and bandpass filters each signal from 0.05Hz-10Hz in order to compute the voltage amplitude features. This simpler feature extraction is used in order to take advantage of the black-box nature of this model.

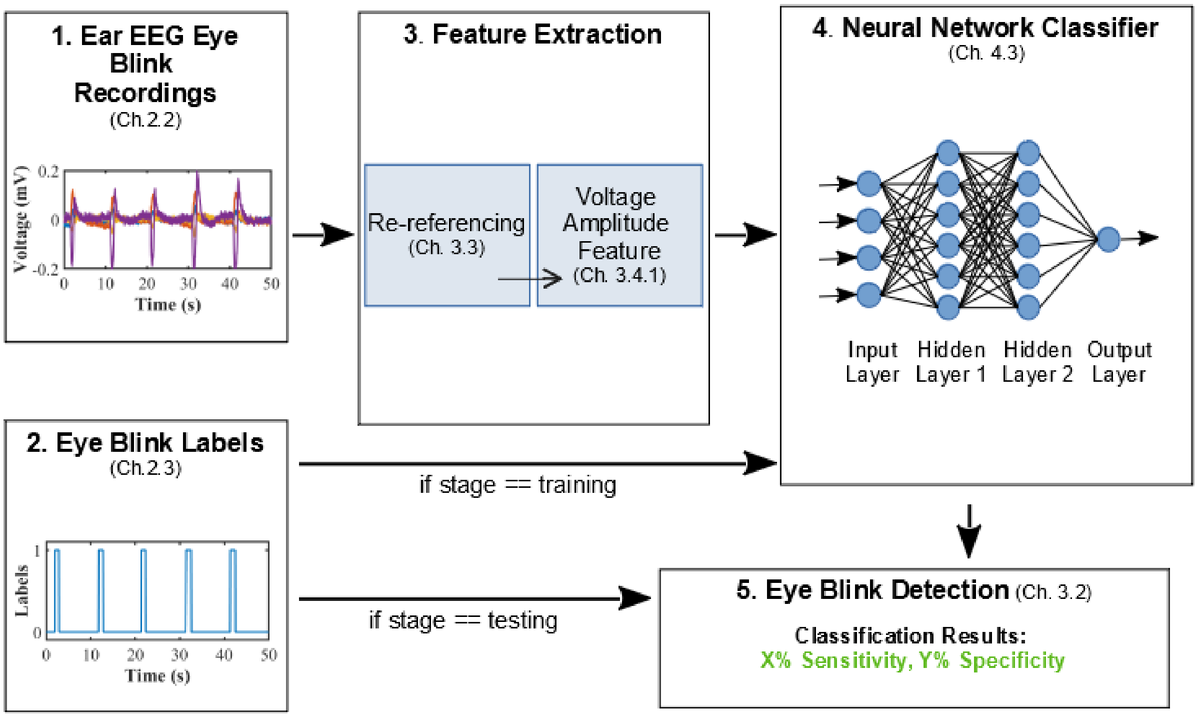

Fig. 4.5. Block diagram for eye blink classification with a neural network classifier.

The neural network implemented in this report classifies eye blinks with 95.2% sensitivity and 98.2% specificity when an average across subjects is calculated according to Equations 3.7 and 3.8. These classification results are not as high as the results of the logistic regression, SVM, or random forest classifiers implemented in this report; however, the neural network classifies eye blink events more effectively using this simple voltage amplitude feature than the other classifier models. The sensitivity of the neural network classifier is approximately 10% higher than the logistic regression and SVM classifiers implemented with this feature and 1.3% higher than the random forest classifier implemented with this feature. This classifier may be an ideal choice for applications where a simple feature extraction block is beneficial or little is known about the relationship between events in a data sets, which makes it challenging to manually design a comprehensive set of features.

4.4 Classifier Comparison Summary

The following table summarizes the eye blink classification sensitivity and specificity results for each subject using the four classifier models detailed in Chapters 3 and 4 (Table 4.1). For the logistic regression, SVM, and random forest models, the classification results are reported when all seven feature calculations explored in Chapter 3 are implemented. For the neural network, the classification results when the simpler feature extraction block presented in the previous section are reported.

Table 4.1

Classifier Results Comparison

Subject	Logistic Regression		SVM		Random Forest		Neural Network	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
1	99.3 %	99.4 %	98.7 %	98.9 %	100 %	99.7 %	94.7 %	98.7 %
2	98.2 %	98.2 %	98.2 %	98.5 %	100 %	99.8 %	99.4 %	99.1 %
3	97.1 %	100 %	97.0 %	100 %	100 %	98.3 %	87.7 %	94.7 %
Average (Eq. 3.7, 3.8)	**98.6 %**	**99.1%**	**98.3%**	**98.9%**	**100%**	**99.5%**	**95.2%**	**98.2%**

From this table, we conclude that the random forest classifier has the highest sensitivity and specificity on average for the eye blink trials recorded with the Ear EEG system in this study. However, all four classifier models are highly effective at identifying the voluntary eye blinks while maintaining relatively high specificity. This allows for choice of classifier model to be made considering other factors, including the amount of training data or computational requirements, in future work that incorporates eye blink classification.

Chapter 5

Summary and Future Work

The eye blink classification results in this report are promising for the use of a user-generic in-ear EEG for eye blink based BCIs. For 500 eye blinks across three subjects, above 95% sensitivity and 98% specificity is reported when logistic regression, SVM, random forest, or neural network classifier models are implemented for eye blink classification. The highest eye blink classification results are achieved with a random forest classifier when seven feature calculations are performed on four recorded and six re-referenced EEG signals. This classifier achieves an average sensitivity of 100% and a specificity of 99.5% across all subjects. Feature selection based on the results reported for eye blink classification when a single feature calculation is considered may allow for the complexity of this classifier to be reduced while achieving similar results, making this classifier more practical for an embedded BCI system.

Of the temporal features analyzed for eye blink classification, the standard deviation ratio feature achieved the highest sensitivity and specificity across all subjects and classifier models with above 96.8% sensitivity and 98.1% specificity in all the considered cases. The peak PSD in the delta band feature achieved the highest sensitivity and specificity of the spectral features considered in this report with 97.1% sensitivity and

99.3% specificity across all subjects and classifier models. These results allow for the implementation of a simple, single feature classifier with high eye blink detection accuracy, which may be useful for applications in which eye blink classification is part of a more complex classification network.

In the process of implementing these eye blink classification algorithms, a reliable classification framework has been set up for the Ear EEG system that can be extended to target the classification of other events in EEG signals. It has been demonstrated in this report that the challenges of reduced spatial covering and reduced SNR of an in-ear EEG system compared to a clinical or EEG headset do not prevent the system from successfully classifying eye blink artifacts. Future work with this system may explore the classification of more complex signals, such as drowsiness, to investigate the applications of a discreet, wearable in-ear EEG system.

References

[1] S. Noachtar et al., “The role of eeg in epilepsy: A critical review,” Epilepsy and Behavior, vol. 15, no. 1, pp. 22–33, 2009.

[2] J. Wu et al., “Utility of eeg measures of brain function in patients with acute stroke,” J. of Neurophysiol., vol. 115, no. 5, pp. 2399–2405, 2016.

[3] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, “BCI2000: A general-purpose brain-computer interface (BCI) system,” IEEE Trans. Biomed. Eng, vol. 51, no. 6, pp. 1034–1043, 2004.

[4] C. Y. Sai, N. Mokhtar, H. Arof, P. Cumming and M. Iwahashi, "Automated Classification and Removal of EEG Artifacts With SVM and Wavelet-ICA," in *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 3, pp. 664-670, May 2018.

[5] G. Schalk et al., “BCI2000: A general-purpose brain-computer interface system,” IEEE Trans. Biomed. Eng, vol. 51, no. 6, pp. 1034–1043, 2004.

[6] M. Duvinage et al., “A p300-based quantitative comparison between the emotiv epoc headset and a medical eeg device,” Biomed. Eng., vol. 765, 5 2012.

[7] G. R. Muller-Putz et al., “Control of an electrical prosthesis with an ssvep-based bci,” IEEE Trans. Biomed. Eng., vol. 55, no. 1, pp. 361–364, 2008.

[8] V. Kartsch, S. Benatti, D. Rossi and L. Benini, "A wearable EEG-based drowsiness detection system with blink duration and alpha waves analysis," *2017 8th International IEEE/EMBS Conference on Neural Engineering (NER)*, Shanghai, China, 2017, pp. 251-254.

[9] M. Teplan, “Fundamentals of EEG measurement,” Meas. Sci. Rev., vol. 2, pp. 1 – 11, 2002.

[10] A. Searle et al., “A direct comparison of wet, dry and insulating bioelectric recording electrodes,” Physiol. Meas., vol. 21, no. 2, pp. 271–283, 2000.

[11] A. Searle and L. Kirkup, “A direct comparison of wet, dry and insulating bioelectric recording electrodes,” Physiol. Meas., vol. 21, no. 2, pp. 271–283, 2000.

[12] V. Mihajlovic, B. Grundlehner, R. Vullers, and J. Penders, “Wearable, wireless EEG solutions in daily life applications: What are we missing?” IEEE J. Biomed. and Health Informatics, vol. 19, no. 1, pp. 6–21, 2015.

[13] P. Kidmose et al., “A study of evoked potentials from ear-EEG,” IEEE Trans. Biomed. Eng., vol. 60, no. 10, pp. 2824–2830, 2013.

[14] D. Looney et al., “The in-the-ear recording concept: User-centered and wearable brain monitoring,” IEEE Pulse, vol. 3, no. 6, pp. 32–42, 2012.

[15] V. Goverdovsky et al., “In-Ear EEG From Viscoelastic Generic Earpieces: Robust and Unobtrusive 24/7 Monitoring,” IEEE Sensors J., vol. 16, no. 1, pp. 271–277, 2016.

[16] A. Paul et al., “Integrated in-ear device for auditory health assessment,” in Conf. Proc. IEEE Eng. Med. Bio., 2019, pp. 56–59.

[17] R. Kaveh *et al.*, “A Wireless, Multielectrode, User-generic Ear EEG Recording System,” *2019 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, Nara, Japan, 2019, pp. 1-4.

[18] R. Kaveh *et al.*, “Wireless User-Generic Ear EEG,” in *IEEE Transactions on Biomedical Circuits and Systems*, vol. 14, no. 4, pp. 727-737, Aug. 2020.

[19] S. Barua, M. U. Ahmed, C. Ahlström, S. Begum, “Automatic driver sleepiness detection using EEG, EOG and contextual information,” *Expert Systems with Applications*, Volume 115, 2019, pp. 121-135, ISSN 0957-4174.

[20] Lotte F, Bougrain L, Cichocki A, Clerc M, Congedo M, Rakotomamonjy A, Yger F, “A review of classification algorithms for EEG-based brain-computer interfaces: a 10 year update,” *Journal of Neural Engineering*, 2018

[21] Stephan Dreiseitl, Lucila Ohno-Machado, “Logistic regression and artificial neural network classification models: a methodology review,” *Journal of Biomedical Informatics*, Volume 35, Issues 5–6, 2002, pp. 352-359.

[22] Mognon A, Jovicich J, Bruzzone L, Buiatti M, “ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features,” in *Psychophysiology*, pp. 229-240, Feb 2011.

[23] Won-Du Chang, Ho-Seung Cha, Kiwoong Kim, Chang-Hwan Im, “Detection of eye blink artifacts from single prefrontal channel electroencephalogram,” *Computer Methods and Programs in Biomedicine*, Volume 124, 2016, pp. 19-30, ISSN 0169-2607.

[24] M. N. Tibdewal, R. R. Fate, Mahadevappa M. and A. Ray, “Detection and classification of Eye Blink Artifact in electroencephalogram through Discrete Wavelet Transform and Neural Network,” *2015 International Conference on Pervasive Computing (ICPC)*, Pune, India, 2015, pp. 1-6.

[25] P. Welch, "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," in *IEEE Transactions on Audio and Electroacoustics*, vol. 15, no. 2, pp. 70-73, June 1967.

[26] Tu, J.. “Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes.” *Journal of clinical epidemiology 49 11 (1996):* 1225-1231.