MED: Muse^{TM}-based Eye-blink Detection Algorithm Using a Single EEG Channel

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***Abstract*— Eye-blinks in electroencephalogram (EEG) signals can be regarded either as unwanted noise or as a source of information. In both cases, a reliable and accurate detector is needed. As many applications require detection and processing of eye-blinks in real-time, detectors are required to be fast and simple. In this work, we have developed a non-learning algorithm for the detection and extraction of eye-blink segments from EEG signals. The signals were recorded by Muse^{TM}, a portable EEG device for recreational use. The proposed algorithm detects eye-blinks via several deterministic processing steps. The algorithm extracts peaks occurring in the EEG signal during the two main eye-blink phases, via extraction of unique features of the EEG eye-blink signal. The proposed algorithm applies various pre-processing steps to ensure robust detection, as well as several sanity-checks to prevent the detection of false peaks and partial eye-blinks. A dataset with recordings of the length of approximately 20 seconds each, taken from few different subjects has been created. The eye-blink annotations were made manually. The proposed algorithm obtains an accuracy rate of 100% on the obtained dataset, while employing a set of deterministic operations which renders it usable in low-resource, real-time applications.**

Keywords*— Biomedical signal processing, Electroencephalogram.

I. Introduction

Eye-blinks are a temporary closure of the eyelids. Eye-blink detection enables a range of applications, especially in healthcare and human-computer interface research. There are numerous existing approaches for eye-blink detection. We identify two main categories of eye-blink detection solutions – Electroencephalogram (EEG) based solutions and non-EEG based solutions. In the non-EEG based category, there exists several approaches. The video-based approach uses data received via a camera positioned in front of the subject to detect eye-blinks visually. Eye-blinks have been detected using the measurement of the maximum velocity of the eyelids for the purpose of detecting driver drowsiness [1]. Although high detection capability is achieved, the system is unusable in certain environmental conditions, such as darkness. Smart glasses embedded with a camera and a processor were also used to detect eye-blinks in a learnable fashion [2]. The employed glasses are resource-limited which enable real-time detection. Nevertheless, the algorithm is data-driven, i.e., there exists a generalization problem, and it is also unusable in dark conditions. Another approach for non-EEG based eye-blink detection is based on the physical characteristics of the eye-blink. For example, employing tiny magnets placed on the upper eyelid, as well as specialized glasses [3]. This approach records the signals originating from the magnets and outputs voltages related to the eyelid movement. The authors achieve high detection accuracy using a deterministic, non-data-driven algorithm which is usable in more diverse conditions, but require the use of designated hardware and magnets to be put on the subject's eyelids, which makes the whole process cumbersome and possibly expensive.

The second main category of eye-blink detection solutions utilize EEG signals. EEG signal recordings enable a look inside the human brain, or at least into its electrical activity. EEG electrodes that are employed on the subject's head measure the electrical activity created by the electromagnetic fields of the neurons in proximity to an electrode [4]. These measurements are usually sensitive to various disturbances. These disturbances can be divided into disturbances caused by the patient's current situation (e.g., fatigue, eye-blinks and stress) and disturbances caused by the surroundings (e.g., electric system noise, electrode moisture). A large amount of effort has been put into the removal of eye-blinks from EEG signal [5, 6]. However, eye-blinks in EEG signals can be viewed as sources of relevant information in various use-cases. As eye-blinks are noticeable in many EEG signal recordings, extracting eye-blink features from EEG signals has presented the ability to predict and monitor neurological conditions, e.g. Alzheimer's disease, strokes, and other nervous system diseases [7, 8].

Traditional EEG systems are physically large, expensive, and cumbersome for usage. Thus, they are usually placed in hospitals and universities for clinical and research use. Due to technological improvements in recent years, user-friendly and cheap EEG systems have been widely available and are used for meditation, biofeedback, research and more [9, 10]. The Muse^{TM} headband is a portable, home-use EEG system containing 5 electrodes for EEG sampling. Muse^{TM} includes a friendly user-interface and developer tools which enable EEG signal recording and processing [11].

Previous work on eye-blink detection in EEG signals was conducted for several applications using different approaches. An unsupervised algorithm was used for the detection of eye-blinks [12], where the algorithm learns the subject's eye-blink pattern and relies on its regularity. While using a single EEG channel, and although impressive results are obtained on several datasets, the algorithm is based on the assumption that a subject exhibits a consistent eye-blink pattern. Such an assumption cannot be made in all cases and instances. Thus, a decrease in performance is observed when irregular eye-blink patterns appear in the data. Different work achieves eye-blink detection based on the frequency-domain features of the EEG signals and to detect drowsiness [13]. In this algorithm the user is required to choose an estimated blinking frequency and relies on this choice for the detection of eye-blinks. Setting such blinking frequency might cause degradation in detection capabilities in the presence of certain neurological conditions during which the eye-blink is of shorter or longer duration than normal. Other approach utilized a 1D convolutional neural-network for the task of detecting voluntary eye-blinks and discriminate them from involuntary eye-blinks for the usage of brain-computer interfaces [14]. The algorithm requires signals from 4 EEG sensors as input, which might be more costly and cumbersome compared to a system which require signals obtained from a single sensor. A generalization problem is also present in the neural-network setting, which might cause degradation of results when testing the network on data from a different distribution than the training data distribution, e.g., new subjects, new neurological conditions, etc.

Eye-blinks are noticeable in EEG signal recordings, as seen in Figure 1, and can be described with respect to the measured baseline voltage. The eye-blink starts with a steep drop in the measured voltage, representing the closing of the eyelid. It is then followed by a steep rise that crosses the baseline and reaches higher voltages, representing the opening of the eyelid. Finally, it is followed by a return to the measured baseline. Eye-blink detection enables the extraction of various features such as eyelid closing and opening voltage amplitudes, peak-to-peak voltage amplitudes and eye-blink duration. These features enable medical professionals to achieve an improved understanding of the patient's neural condition [7, 8].

In this work, we present a novel approach to eye-blink detection in EEG signals acquired by the Muse™ headband device. An EEG dataset is recorded consisting of recordings from 3 different subjects. The proposed algorithm performs signal processing in the time-domain, preventing the overhead of applying transforms to the signals prior to processing. Consisting deterministic and low-complexity steps, the proposed method achieves 100% accuracy on the acquired dataset with 0 false-positives. Moreover, the proposed method demonstrates short run-time while making only few assumptions on input signals, making it robust to variations in inter-subject and intra-subject eye-blink patterns.

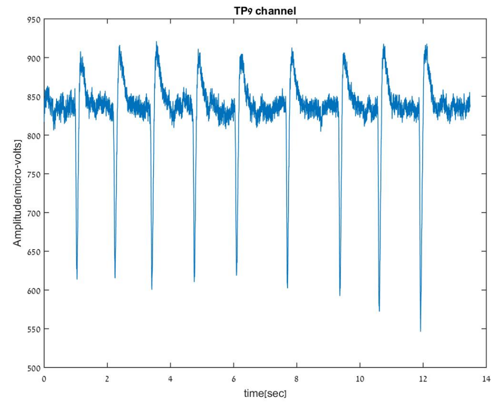

Figure 1. A short recording from TP9 electrode of the Muse™ headband. Prominent minimum peaks, followed by the related maximum peaks, represent eye-blinks.

II. Eye-blink detection algorithm

In this section, we elaborate the two main stages in the proposed eye-blink detection algorithm: preprocessing and detection.

II-A. *Preprocessing*

The preprocessing stage consists of numerous steps. First, local minima of the time-domain signal (represented in voltages) are found in the raw signal. These minima represent the initial estimates of the eye-blinks' locations, and are found with two constraints: Minimum distance and minimum voltage difference. (1) A minimum distance of 0.1 seconds between every two peaks. This constraint is regarded as the minimum eye-blink time and prevents the detection of secondary peaks found on main peaks that occur due to noise. (2) The local minimum is at least 70μV below the baseline of the signal (which is calculated as the mean of the signal). This constraint prevents the detection of small peaks which are not eye-blinks, but rather represent noise. The 70μV threshold was empirically selected. The next preprocessing step is centering and filtering during which the input signal is normalized to have zero mean, and then filtered twice. The first filter is an exponential moving average filter, defined as:

$$y[n] = \alpha x[n] + (1-\alpha) y[n-1] \tag{1}$$

Where $y[n]$ is the output of the filter at time-step n, $x[n]$ is the input to the filter at time-step n, and α is the weight. The proposed algorithm uses $\alpha = 0.1$. The second filter is the standard moving average filter, defined as:

$$y[n] = \frac{1}{L}(x[n] + x[n-1] + ... + x[n-L+1]) \tag{2}$$

Where $y[n]$ and $x[n]$ are defined as above, and L is the window size of the filter, which was set to be 0.01 seconds. This combination of filters was empirically found to provide optimal smoothing of the signal in terms of noise suppression and keeping the eye-blink peaks prominent. The smoothing of the signal reduces the signal's amplitude significantly. Therefore this step is performed following the obtaining of the initial minima points, since amplitude differences before filtering are considerably greater. The final preprocessing step is the removal of partial eye-blinks which occurred at the beginning or the end of the signal. These partial eye-blinks usually occur due to recording which begin or finish during an eye-blink, providing partial information which is unusable for our intended use case. The partial information makes these partial eye-blinks irrelevant for most applications and the proposed algorithm removes them. The detection and removal of these occurrences is done in three steps:

1) Scan the signal from the beginning of the recording to the first minima, found in the first preprocessing step. If the amplitude was never close to zero (greater than -5 μV), it indicates that the recording started during the first phase of the eye-blink, i.e., the closing of the eyelid. This eye-blink is therefore deleted.

2) For each minimum found at the first step, a matching maximum, i.e., the opening of the eyelid, is found. The proposed algorithm searches for the maximum inside a window to the right of the minimum, where the window's size is chosen to be the minimum between the time to the next minima and 0.5 seconds. This time frame is considered as the upper limit of the eye-blink time. This step is also used as a sanity check on the found minima. If the maximum inside the window is smaller than a threshold of 15μV, this eye-blink is removed.

3) Scan the signal from the last maximum to the end. If the amplitude was never close to zero, i.e., smaller than 5 μV, it indicates that the recording ended before the eye-blink ended. This eye-blink is therefore deleted.

II-B. Detection

Given the minima and maxima found in the previous stage as reference points for the main eye-blink phases, i.e., the closing and the opening of the eyelid, the decision on the beginning and end times of each eye-blink is done similarly to the partial eye-blink removal step. The beginning time of the eye-blink is selected as the last time-point where the amplitude was close enough to zero, i.e., greater than -5 μV, before the minimum of the eye-blink. The end time is selected as the first time-point where the amplitude was close enough to zero, i.e., smaller than 5 μV, after the maximum of the eye-blink. These time-points represent the beginning of the eyelid closing and the end of the eyelid opening, respectively.

The general pipeline of the proposed algorithm is depicted in Figure 2 and summarized in Algorithm 1.

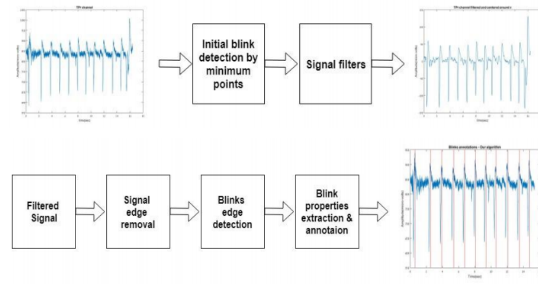

Figure 2. The proposed algorithm pipeline.

Algorithm 1 Proposed eye-blink detection algorithm

Preprocessing:

1) Detect local minima on raw time-domain signal with constrains:
   - Minimum distance of 0.1 seconds between every two peaks.
   - Minima are at least 70μV below the baseline of the signal (calculated as the mean of the signal).
2) Normalize the signal to zero mean.
3) Filter the signal twice using the following filters:
   - Exponential moving average filter with $\alpha = 0.1$.
   - Standard moving average filter with 0.01 seconds window length.
4) For each minima find its matching maxima and remove partial eye-blinks that might occur in the beginning or the end of the signal:
   - Scan the signal from the beginning of the recording to the first minima. If the amplitude never got values greater than -5 μV, remove the eye-blink.
   - For each minimum point found, find a matching maximum. Search for the maximum inside a window to the right of the minimum, where the window's size is chosen to be the minimum between the time to the next minimum point and 0.5 seconds. If the maximum inside the window is smaller than a threshold of 15μV, this eye-blink is removed.
   - Scan the signal from the last maximum to the end, if the amplitude was never smaller than 5 μV remove the eye-blink.

Detection:

1) For each minimum and it's matching maximum points found in the preprocessing step:
   - Set the eye-blink beginning time as the last time-point before the minimum where the amplitude is greater than -5 μV.
   - Set the eye-blink end time as the first time-point after the maximum where the amplitude is smaller than 5 μV.

III. Experiments

The data for all experiments was collected via Muse™ 2014 device. The EEG signals are recorded by 4 channel electrodes, located at channels TP9, AF7, AF8 and TP10 at a sampling rate of 220 Hz. The proposed algorithm uses the data from a single channel. TP9 and TP10 channels are more relevant to the task of eye-blink detection as they are located closer to the eyes. Using both these channels might be the trivial solution, and we have considered that option, but decided to arbitrarily select TP9 channel. The dataset consists of recordings from 3 different test subjects, with a total recording time of 200 seconds split over 12 sessions. Annotations of the eye-blinks were manually made in order to ensure correctness of results. Test subjects were requested to blink naturally while performing no other actions during recording session.

The proposed algorithm was tested on an Intel® Core™ i7 CPU with 4 GB RAM. MuseIO was used as the driver for transferring the data from Muse™ headband to the computer, and MuseLab was used as the interface software. The algorithm was written and tested using MathWorks® MATLAB 2015a.

IV. Results and discussion

The proposed algorithm achieves 100% accuracy in detecting eye-blinks in the dataset, without any occurrences of false positives, i.e., no false detection of eye-blinks that did not occur. Figure 3 shows a visualization of the proposed algorithm output on one segment from the dataset, over the raw signal.

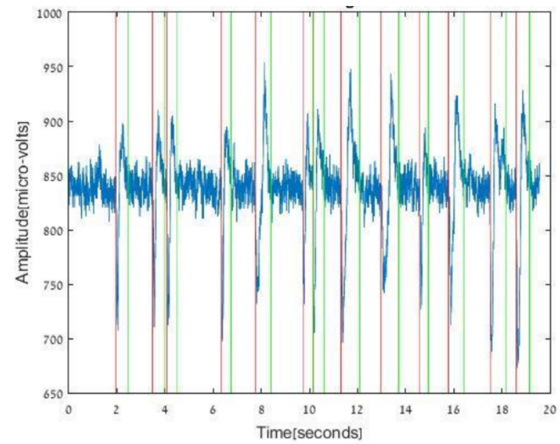

Figure 3. An example of the proposed algorithm output. A red line indicates an inferred eye-blink start time, and the consecutive green line indicates the inferred end time for the same eye-blink.

As seen in the figure, the proposed algorithm accurately detects the beginning and end times of each eye-blink, including eye-blinks that are in proximity to one another.

Comparing to other eye-blink detection methods [2, 3, 12, 13], the proposed algorithm achieves superior results, while employing a low complexity, unsupervised scheme which is applicable in real-time and uses minimal hardware (a single EEG channel). The proposed algorithm is not affected by the generalization problem and is usable in dark lighting conditions, unlike other methods [2]. Other work required designated hardware [3], including magnets which must be placed on the subject's eyelids. The proposed algorithm utilizes a consumer off-the-shelf product that is conveniently put on the subject's forehead. While previous work had an assumption on the consistency of eye-blink patterns [12], the proposed algorithm does not rely on any assumptions regarding the regularity of eye-blink patterns.

For conducting a relevant comparison of the proposed algorithm results, two additional algorithms have been tested using our dataset: Muse™ automatic eye-blink detection algorithm, and a frequency-domain based method [13] for drowsiness detection. The latter depends on the selection of short-time Fourier transform (STFT) parameters and the estimated eye-blink frequency. Results are summarized in Table 1.

As seen in the table, the proposed algorithm achieves superior results in both accuracy and false positive rates. Muse™ eye-blink detection algorithm presents a large rate of false positives, mainly due to falsely detecting one eye-blink as several eye-blinks, i.e., making duplicate detections. It can also be seen that the drowsiness detection algorithm [13] is more robust in terms of false positives than Muse™ algorithm. The drowsiness detection algorithm [13] detection accuracy is lower than other methods on our dataset. This accuracy result was achieved after experimenting with the eye-blink estimated frequency which is required as input to the algorithm. It is possible that other values might achieve higher accuracy. Nevertheless, the proposed algorithm obtains 100% accuracy and zero false positive on the same dataset, without the need to choose input parameters.

Table 1. Results comparison of the proposed algorithm and two other algorithms

Algorithm	Accuracy	False positive (%) of total
Muse™	96.8%	24 (18%)
Drowsiness Detection [13]	72.3%	14 (11%)
Proposed	100%	0 (0%)

V. Conclusions

In this work, we have developed an accurate eye-blink detection algorithm from EEG signals acquired from a single sensor channel. The proposed method can work with any commercial off-the-shelf EEG sensor, and is based on several fast deterministic operations. This renders the proposed algorithm usable in real-time, low-resource applications. The algorithm is not data-driven and makes very few assumption on the input signal. This might allow for better generalization to new test subjects and more challenging eye-blink detection cases. The proposed dataset was obtained as a preliminary proof-of-concept, and the proposed algorithm achieves a rate of 100% accuracy in eye-blink detection, as well as zero false positives.

Future work should include testing the algorithm on a larger, more diverse dataset. Moreover, applying dynamic detection thresholds as well as combining results from two sensors. More sensors might achieve more robust detection capabilities and could demonstrate better performance. Another possible research direction would be to use the algorithm as a preliminary step for other applications which require the eye-blinks detection, such as human identity verification based on EEG eye-blink signals.

REFERENCES

[1] M. H. Baccour, F. Driewer, E. Kasneci, and W. Rosenstiel, "Camera-based eye blink detection algorithm for assessing driver drowsiness," *2019 IEEE Intelligent Vehicles Symposium (IV)*, 2019, pp. 987–993.

[2] H. Le, T. Dang, and F. Liu, "Eye blink detection for smart glasses," *2013 IEEE International Symposium on Multimedia*, 2013, pp. 305–308.

[3] A. Hanuka, M. Itzhak, A. Berger, M. Orbach, E. Shoshan, L. Schächter, and D. Briscoe, "A novel eyelid motion monitor," *Albrecht von Graæes Archiv für Ophthalmologie*, vol. 255, 09 2017.

[4] J. S. Kumar and P. Bhuvaneswari, "Analysis of electroencephalography (eeg) signals and its categorization–a study," *Procedia Engineering*, vol. 38, pp. 2525–2536, 2012, iNTERNATIONAL CONFERENCE ON MODELLING OPTIMIZATION AND COMPUTING. (available at: *https://www.sciencedirect.com/science/article/pii/S1877705812022114*).

[5] A. Borowicz, "Using a multichannel wiener filter to remove eye-blink artifacts from eeg data," *Biomedical Signal Processing and Control*, vol. 45, pp. 246–255, 2018. (available at: *https://www.sciencedirect.com/science/article/pii/S1746809418301149*).

[6] S. Phadikar, N. Sinha, and R. Ghosh, "Automatic eyeblink artifact removal from eeg signal using wavelet transform with heuristically optimized threshold," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 2, pp. 475–484, 2021.

[7] D. Woodruff-Pak, "Eyeblink classical conditioning differentiates normal aging from alzheimer's disease," *Integrative physiological and behavioral science : the official journal of the Pavlovian Society*, vol. 36, pp. 87–108, 04 2001.

[8] B. D, "Blink rate behavioral pattern changes in patients affected by acute stroke: A cross-sectional study," *Archives in Neurology & Neuroscience*, vol. 5, 09 2019.

[9] J. LaRocco, M. D. Le, and D.-G. Paeng, "A systemic review of available low-cost eeg headsets used for drowsiness detection," *Frontiers in Neuroinformatics*, vol. 14, p. 42, 2020. (available at: *https://www.frontiersin.org/article/10.3389/fninf.2020.553352*).

[10] S. A. Memon, A. Waheed, T. Başaklar, and Y. z. Ider Ider, "Low-cost portable 4-channel wireless eeg data acquisition system for bci applications," *2018 Medical Technologies National Congress (TIPTEKNO)*, 2018, pp. 1–4.

[11] O. E. Krigolson, C. C. Williams, A. Norton, C. D. Hassall, and F. L. Colino, "Choosing muse: Validation of a low-cost, portable eeg system for erp research," *Frontiers in Neuroscience*, vol. 11, p. 109, 2017. (available at: *https://www.frontiersin.org/article/10.3389/fnins.2017.00109*).

[12] M. Agarwal and R. Sivakumar, "Blink: A fully automated unsupervised algorithm for eye-blink detection in eeg signals," *2019 57th Annual Allerton Conference on Communication, Control, and Computing (Allerton)*, 2019, pp. 1113–1121.

[13] 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)*. IEEE, 2017, pp. 251–254.

[14] M. Lo Giudice, G. Varone, C. Ieracitano, N. Mammone, A. R. Bruna, V. Tomaselli, and F. C. Morabito, "1d convolutional neural network approach to classify voluntary eye blinks in eeg signals for bci applications," *2020 International Joint Conference on Neural Networks (IJCNN)*, 2020, pp. 1–7.