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# MED: Muse™-based Eye-blink Detection Algorithm Using a Single EEG Channel

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# Presentation outline

- Introduction
  - Problem definition
  - Previous work
- Proposed algorithm
  - Preprocessing
  - Detection algorithm
- Results
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# Problem Definition

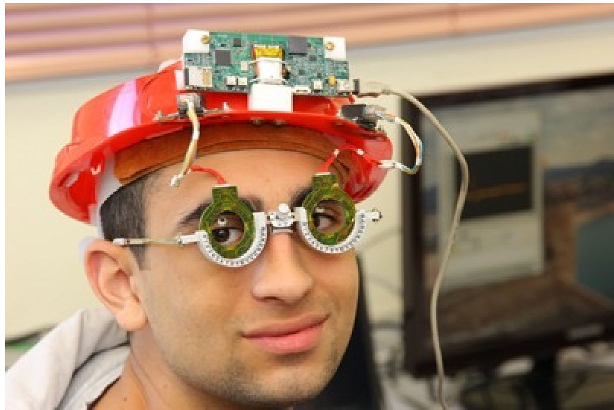
Reliable eye-blinks detection which can be used in real-time

Non-EEG based methods

EEG based methods

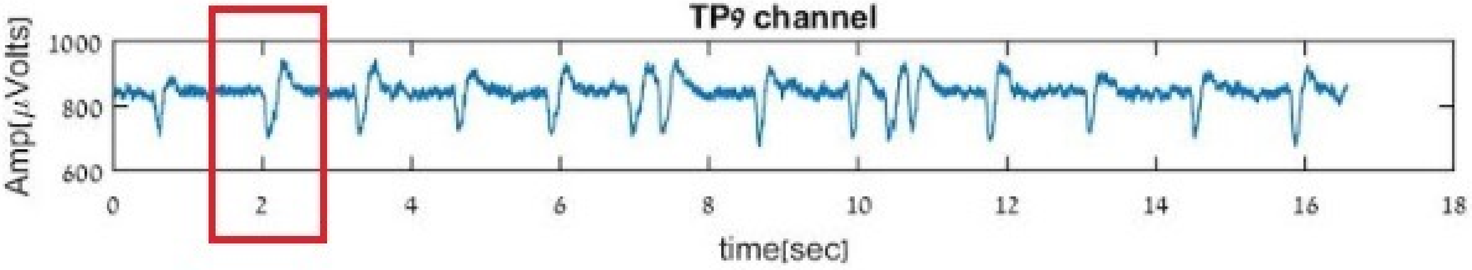
# Previous work – Non-EEG Methods

- Video based approach [1]
  - High detection capabilities
  - Unusable in darkness and other environmental conditions
- Smart glasses embedded with a camera and a processor [2]
  - Real time detection
  - Data driven (learning algorithm)
  - Unusable in dark conditions
- Tiny magnets on upper eyelid with specialized glasses [3]
  - High accuracy
  - Deterministic and usable in diverse environmental conditions
  - Special hardware – cumbersome and expensive



# Eye blinks in EEG signals

- Reliable eye-blinks detection in EEG signals which can be used in real-time
- Eye-blinks detection for removal from EEG signals [5, 6]
- Eye-blinks in EEG signals can also be viewed as sources of information
- Eye-blink features extraction from EEG signals might predict and monitor neurological conditions such as Alzheimer's disease, stroke, and other nervous system diseases [7, 8]



# Previous work – EEG Methods

- Muse™ automatic eye-blink detection algorithm
  - No implementation details
- Drowsiness detection using frequency-domain features [13]
  - Estimated blinking frequency is mandatory for eye-blinks detection
  - User specific, hard to estimate for neurological conditions
  - Requires STFT parameters tuning
- Discriminating voluntary and involuntary eye-blinks using 1D CNN [14]
  - Used for brain-computer interfaces (BCI)
  - Input signals from 4 EEG sensors
  - Inherent generalization problem in data-driven neural network setting

# Proposed algorithm

- Novel approach for eye-blinks detection in EEG signals acquired by Muse™
- Preliminary EEG dataset with recordings from 3 different subjects was acquired for algorithm proof of concept (POC)
- The proposed algorithm performs signal processing in the time-domain
  - Deterministic and low-complexity steps
  - Robust to variations in inter-subject and intra-subject eye-blink patterns
  - Short run-time
  - Though small POC dataset - 100% accuracy with 0 false-positives

# Proposed algorithm – Signal example

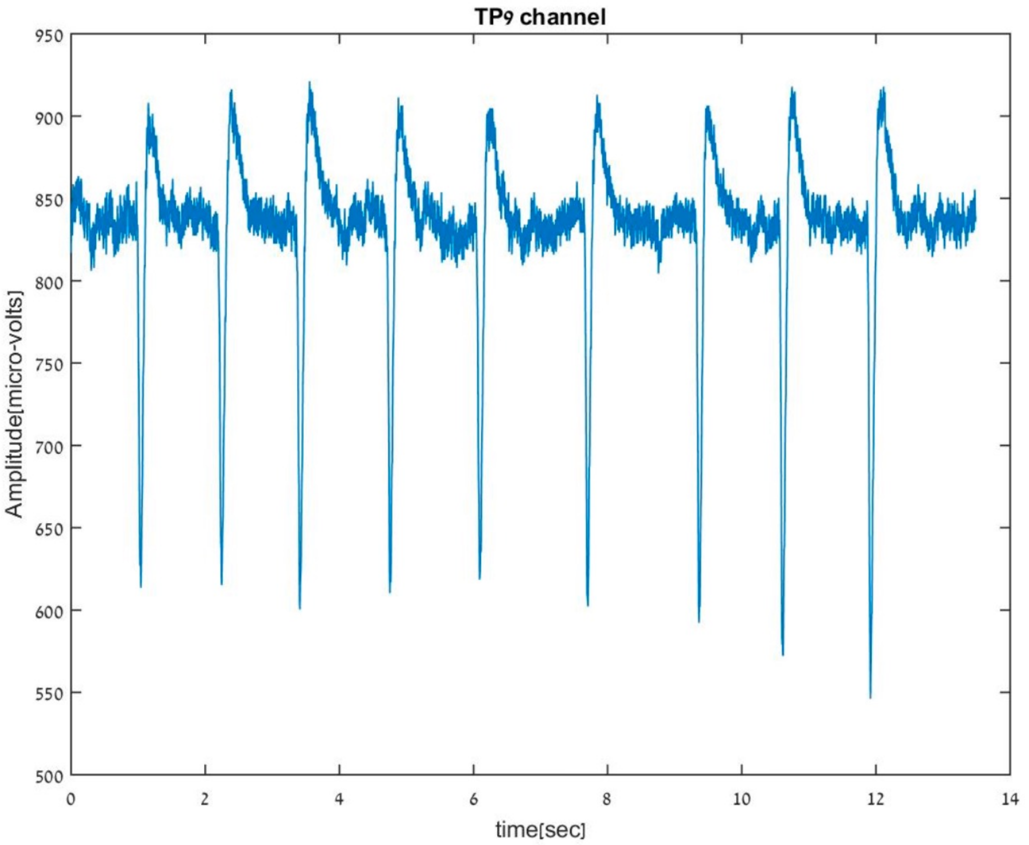
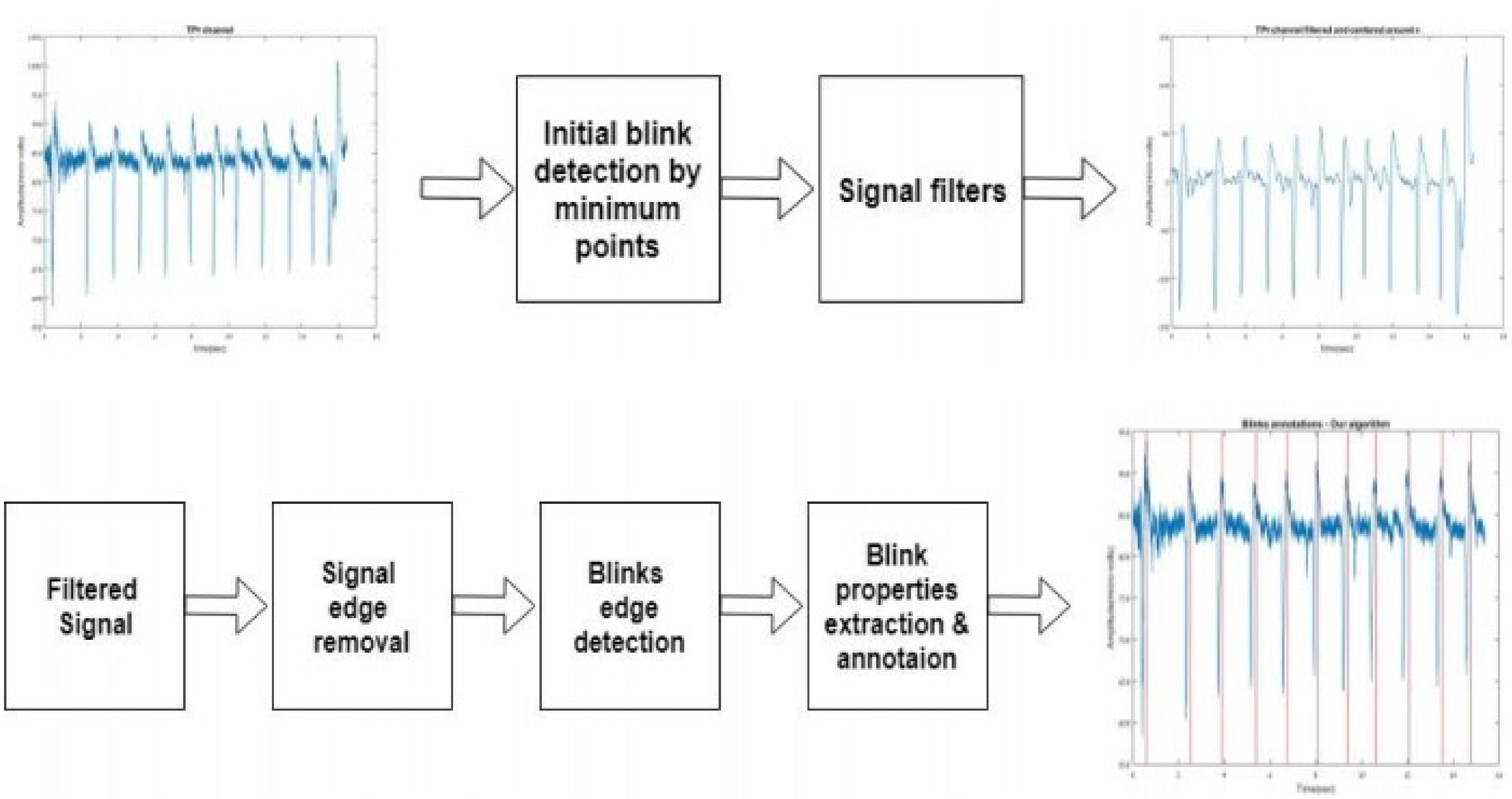


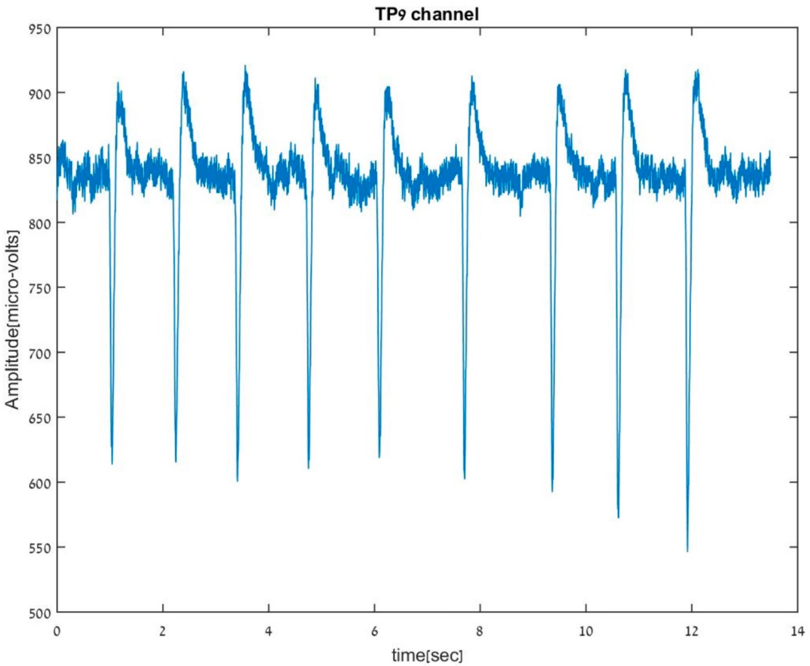

Figure 1. A short recording from TP9 electrode of the Muse™ headband. Prominent minimum peaks, followed by the related maximum peaks, represent eye-blinks.

# Proposed algorithm – Block diagram



# Preprocessing

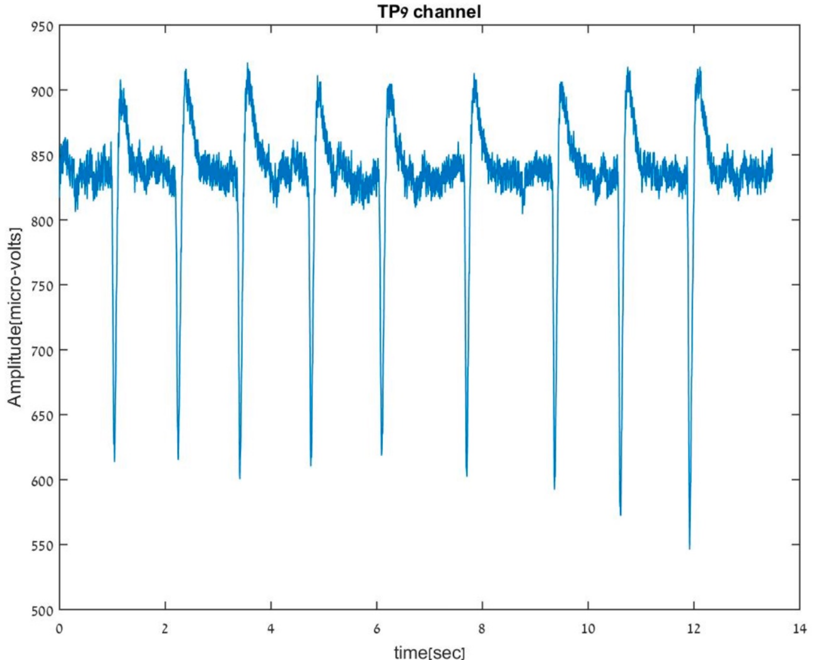
1. Detect local minima on raw time-domain signal with constrains:
    1. Minimum distance of 0.1 seconds between every two peaks
    2. Minima are at least 70μV below the signal baseline (mean)
2. Normalize the signal to zero mean
3. Filter the signal twice using the following filters:
    1. Exponential moving average filter with $\alpha = 0.1$:
    $$y[n] = \alpha x[n] + (1-\alpha) y[n-1]$$
    2. Standard moving average filter with L = 0.01:
    $$y[n] = \frac{1}{L}(x[n] + x[n-1] + \ldots + x[n-L+1])$$
4. Remove partial eye-blinks (described in next slide)



# Preprocessing – Partial eye-blinks removal

For each minima find its matching maxima and remove partial eye-blinks that might occur in the beginning or the end of the signal:

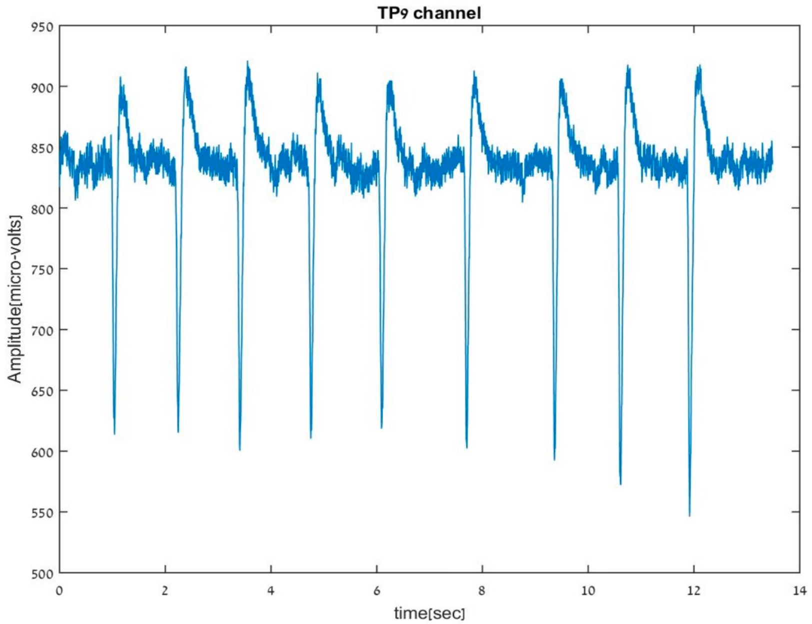
1. Scan the signal from the beginning of the recording to the first minima. If the amplitude never got values greater than -5 µV, remove the eye- blink.
2. Detect blink segments - for each minimum point found, find a matching maximum.
3. Scan the signal from the last maximum to the end, if the amplitude was never smaller than 5 µV remove the eye-blink.



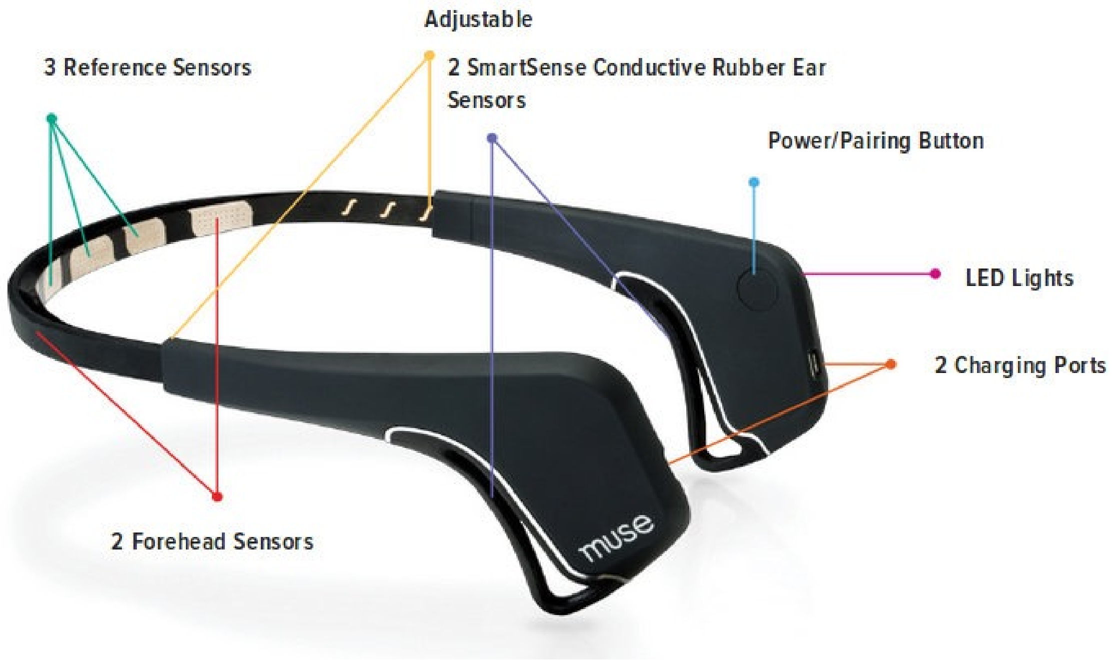
# Detection

For each minimum and it’s matching maximum points found in the preprocessing step:

1. Set the eye-blink beginning time as the last time point before the the minimum where the amplitude is greater than $-5\mu V$
2. Set the eye-blink end time as the first time point after the maximum where the amplitude is smaller than $5\mu V$



# Muse™ Headband

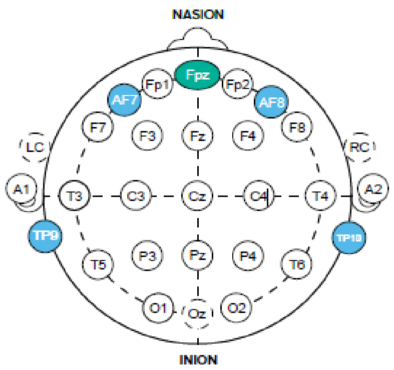


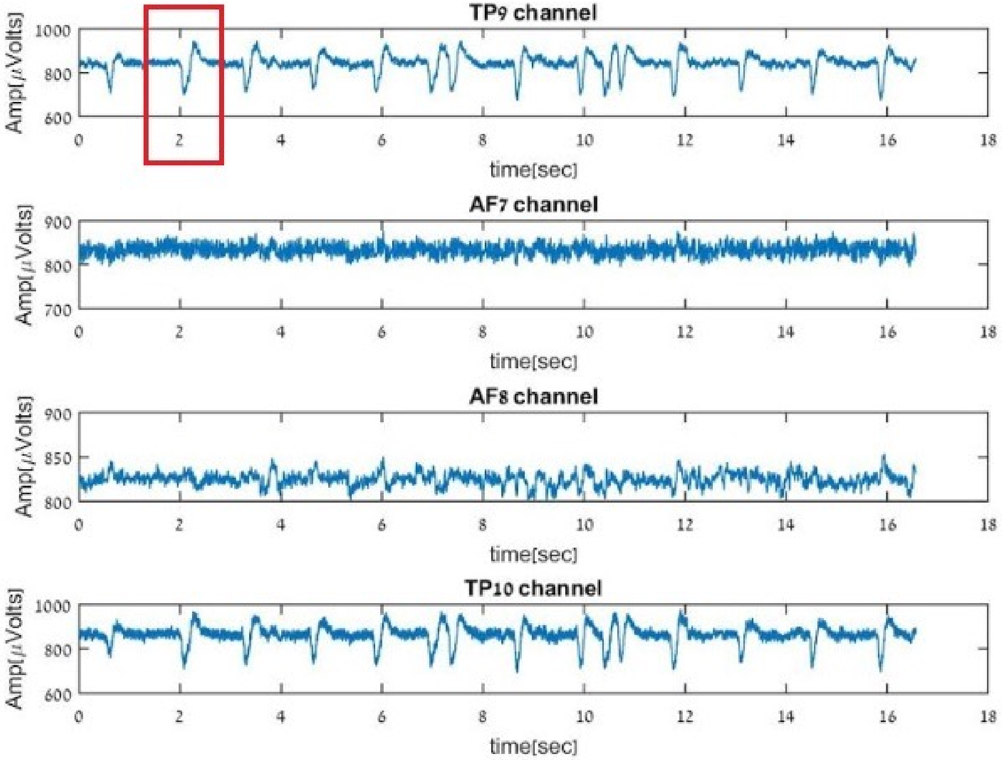
# Experiments – Data acquisition

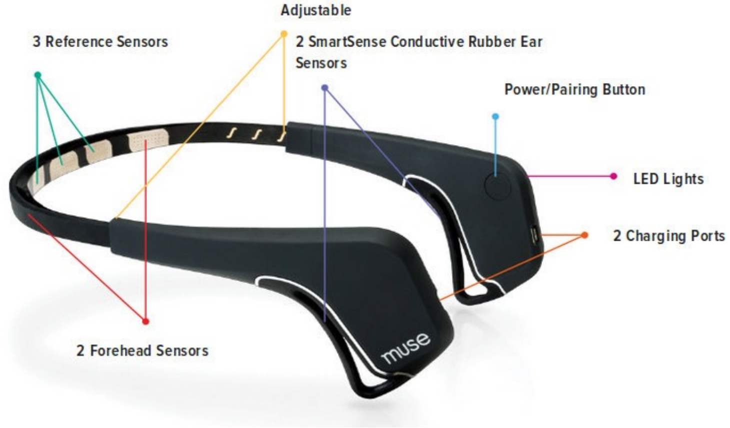
Muse electrode locations by 10-20 International Standards.

Reference

Channel

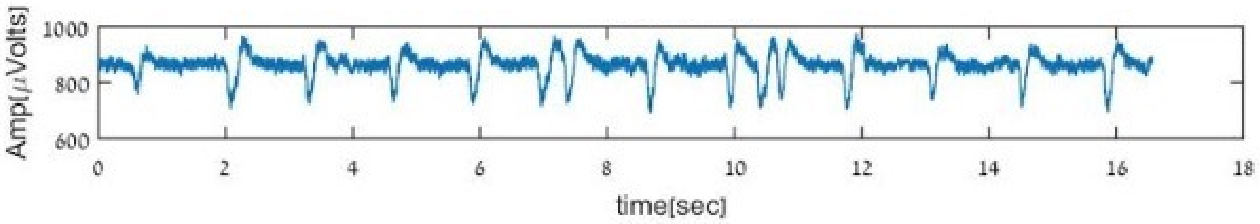


# Experiments – POC dataset

- Proof of concept (POC) dataset consists recordings from 3 different subjects
- Total recording time of 200 seconds split over 12 sessions
- Eye-blinks were manually annotated in synch with video recording
- Subjects were requested to blink naturally while performing no other actions during recording sessions




# Results

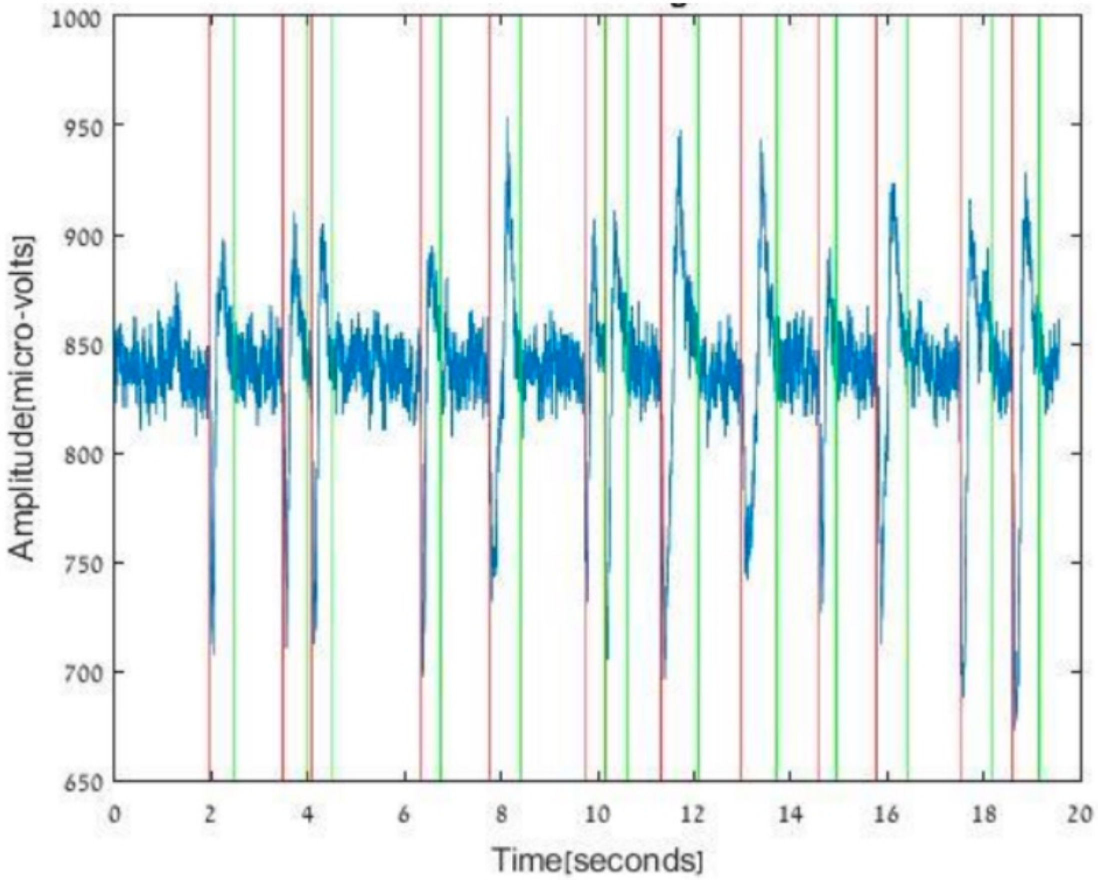



Figure 3. An example of the proposed algorithm output. A red line indicates an inferred eye-blink start time, and the consecutive green line indicates the inferred end time for the same eye-blink.

# Results - Comparison

Two additional algorithms were tested using our POC dataset:

1. Muse™ automatic eye-blink detection algorithm
2. Frequency-domain based method [13] for drowsiness detection

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%) |

# Conclusions

- Reliable eye-blinks detection algorithm from a single EEG channel
- Based on several fast deterministic operations, allowing it real-time usability
- Not data-driven and requires very few assumption on the input signal
- 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

- Testing the algorithm on a larger, more diverse dataset
- Applying dynamic detection thresholds
- More channels might achieve more robust detection capabilities and could demonstrate better performance
- Use the algorithm as a preliminary step for other applications which require eye-blinks detection, such as human identity verification based on EEG eye-blink signals

# Thank you for your time!

# Questions?

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