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An Interface using Electrooculography with Closed Eyes

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Abstract: The purpose of our study was to determine the electrooculography (EOG) interface that can be used for amyotrophic lateral sclerosis (ALS) patients that can use without preparation. We proposed eye movement detection using Root Mean Square the active threshold (AT method) and k-nearest neighbor (k-NN) methods. The AT method is the threshold method that is dynamically calculated using the root mean square. This report describes the combined use of both methods. We conducted experiments on the waveform detection accuracy for 19 healthy subjects between the ages of 20 and 29 years. The hit rate for the proposed method was 94%, and the FA rate was 9%. Next, we calculated the information transfer rate (ITR), a popular evaluation index in for the brain-computer interface. (BCI). The minimum ITR using the proposed method was 19.02[bits/min]. The ITR of the P300 speller a BCI tool, was 16.4[bits/min]. The ITR of the proposed method was higher than that using the P300 speller. Therefore, it can be said that the proposed method has usefulness as an interface.

Keywords: Bio-signal switch, EOG, ALS

1. INTRODUCTION

Studies have reported that patients with neurological diseases who have become tetraplegic can operate instruments using their remaining functions with the help of a bio-signal interface [1]. However, the symptoms and degrees of progression of these diseases differ from individual to individual patient. For example, amyotrophic lateral sclerosis (ALS), a neurological disease, causes muscular atrophy and weakness throughout the entire body; however, ALS patients might be able to use electrooculography (EOG) to control specific devices.

EOG signals differ greatly among individuals in both large signal dispersion and some artifacts, such as eye blinks, and other signal variations; therefore, when using EOG as a interface, it is necessary to first classify it using voluntary and involuntary eye movements. This classification has been studied in previous research. For example, Saito [2] has classified voluntary eye blinks with an accuracy of 98% in support vector machines used to control electric wheelchairs. Dhanush et al. [3] have described five classifications of upward, downward, left, right, and blinking with an accuracy of 80% for keyboard operation. These studies have resulted in the creation of specialized individualized eye movement detectors; however, although these are highly accurate, measurements and adjustments to the detectors must be done in advance by experts. For example, in Saito's blink classification study, the number of 1,600 voluntary and involuntary blinks was summed over 4 d, and 100 pieces of data were randomly extracted as training information [2].

The results of the Dhanush study created thresholds for

classification from preliminary experiments [3]. Precise adjustment of thresholds requires expert knowledge and skill, which cannot be easily done by the patients. Thus, we investigated the active threshold (AT) method, which dynamically calculates the threshold, and the k-nearest neighbor (k-NN) method, providing classifications [4] [5] to resolve this problem. This report describes the current study on an intentional transfer interface using EOG that combines these two methods.

2. MEASUREMENTS AND EVALUATION

In the current study, the action "close eyes and turn upward" was set as the input action [6]. The EOG electrode was attached to the right earlobe of the reference electrode (reference), which was ~1 cm below the right eyeball, and the ground for the filter was attached to the left earlobe. Figure 1 shows the flow in the experiment. Both the motion and rest sections in Fig. 1 were set to 5 sec. Each subject was measured 10 times. There were 20 trials from 15 subjects. The open source BCI (OpenBCI) module was used for to record the electrical activity. The number of movement detections was recorded as an index of waveform detection accuracy (Table 1), and the Hit rate and FA rate were calculated (using Eqs. 1, and 2).. The higher the Hit rate, the better the performance, and the lower the FA rate, the better the result.

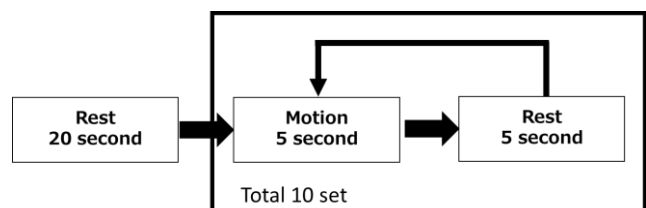


Figure1: Measurement of flow

Table 1: Record of output

| | Output | |
|-----------------------|-------------|-------------------|
| | High | Low |
| Intentional Action | Hit | Miss |
| Nonintentional Action | False Alarm | Correct Rejection |

$$\text{Hit rate}(\%) = \frac{\text{Hit}}{\text{Hit} + \text{Miss}} \times 100 \quad (\text{Eq.1})$$

$$\text{FA rate}(\%) = \begin{cases} \frac{\text{FA}}{\text{FA} + \text{CR}} \times 100 \dots (\text{FA} > 0) \\ \frac{0.5}{\text{FA} + \text{CR}} \times 100 \dots (\text{FA} = 0) \end{cases} \quad (\text{Eq.2})$$

3. ACTIVE THRESHOLD (AT) METHOD

3.1 Calculating the Active Threshold

The AT method can dynamically calculate the threshold value from the eye's electrical potential. First, a Root Mean Square (RMS), the effective value of the signal, is calculated. $RMS(t)$ is calculated using EOG between w sec before the current eye potential $EOG(t)$. The effective RMS value indicates the intensity per unit time of the alternative current (i.e., AC) signal. RMS can be calculated from the eye potential of each individual. The AT method derives a threshold by multiplying $RMS(t)$ by a constant. The threshold value is obtained using Eq. 4. If the $EOG(t)$ exceeds the threshold $AT(t)$, the output state is high (Eq. 5). In this study, the experiment was conducted using RMS from the last 2 sec and a 3.5 in Eqs. 3, and 4.

$$RMS(t) = \sqrt{\frac{1}{N} \sum_{k=N-w}^N EOG(k)^2} \quad (\text{eq.3})$$

$$AT(t) = a \times RMS(t) \quad (\text{eq.4})$$

$$\text{output state} \begin{cases} \text{High} \dots EOG(t) \geq AT(t) \\ \text{Low} \dots EOG(t) < AT(t) \end{cases} \quad (\text{eq.5})$$

3.2 Results

19 out of 20 trials were effective, mean hit rate and FA rate were 79% and 12%, respectively. In a report by Okamura [7] on manipulating equipment using blinks, the success rate for those who first operated biological signals was ~ 80%. In this experiment, 14 out of 20 trials consisted of people who used the equipment for the first time, the average success rate is 79%, which suggests that the AT method is effective. Figure.2 shows the hit detection rate from a successful example. The y axis represents the EOG (μV) potential of EOG [μV] and the x axis represents the time (sec), which is time from 0 sec after patients were instructed. The solid line is the eye potential and the dashed line is the AT. As indicated, AT changed with changes in

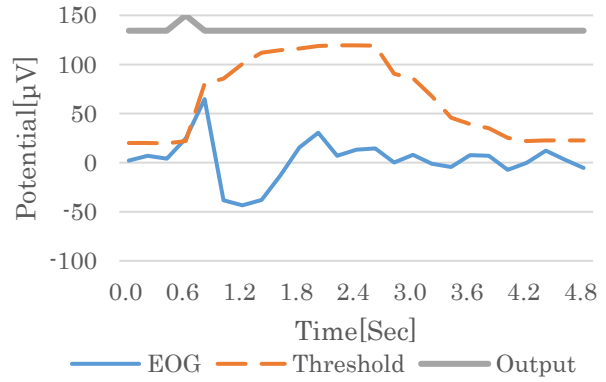


Figure.2: Waveform of a hit detection using the active threshold method.

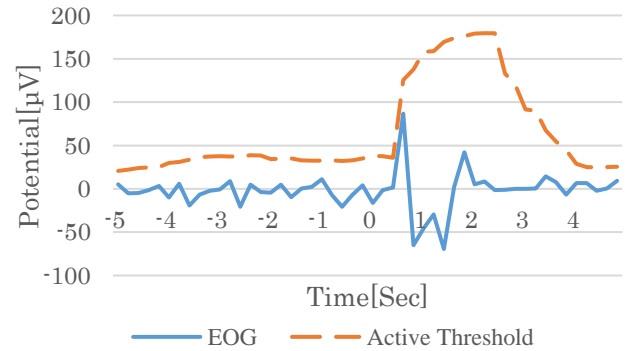


Figure.3: Waveform of a Miss detection using the AT method

EOG. On the other hand, because the AT method derives a threshold value from EOG, it is observed to be vulnerable to signal fluctuations, as shown in Fig. 3. Measurements were taken from 0 sec and show that a change in EOG potential occurred from that point. However, it was not detected in this section. In Fig. 3, EOG potential fluctuates and the threshold values begin to change, which increase as EOG potential decreases. With the AT method, RMS is used for calculating the threshold value, therefore, the threshold increases from EOG fluctuation, and it is considered that the omission of detection has occurred. Thus, waveform detection that can support the AT method was examined.

4. K-NEAREST NEIGHBOR (k-NN) METHOD

4.1 About the k-NN method

The k-nearest neighbor (k-NN) method is one of pattern recognition that classifies responses using vector space distance. In this study, responses were classified using Euclidean distances, which is the space value between two points calculation. The k-NN method enables stable operations even with little training data and has a relatively high classification performance. We reported EOG classification using the k-NN method offline. In the current

study, we conducted experiments using the k-NN method in for online classification. The parameter k was set to 5. The k-NN method was used to add OpenBCI to the experiment.

4.2 Result

The mean hit and FA rates using pseudo-online detection on 19 trial log effective data were 93% and 8%, respectively. Figure 4 shows one of the waveforms detected using the k-NN method. We can see that the k-NN method can detect the EOG changes related to eye motion.

Both the hit and the FA rates were better than those using the AT method. However, when comparing the two methods, we found a difference in the waveforms that can be detected using each method. An example in which waveforms cannot be detected using the k-NN method is shown in Fig. 5 using measurements from 0 sec. This EOG power is smaller than that in the other section; however, the waveforms can be detected using the AT method even when the EOG potential is low as long as it is changing. From this, we found that the k-NN method cannot detect waveforms if the EOG potential is low; therefore, we believe that improving the detection accuracy can be achieved using both methods in combination.

5. The parallel Method (AT +k-NN)

5.1 The Parallel Method

To improve the accuracy of waveform detection, a combination of both methods was examined. One issue with the combined use is the difference in each in the time needed to detect waveforms. Between the two methods, the detection time of the AT method is faster at 1.7 sec than that of the k-NN method. Therefore, by setting a waiting time of 2 sec for the AT method, a state of waiting to judge the k-NN method was created. If it was determined that the waveforms using the k-NN were detected within 2 sec after those using the AT method were detected, the output was generated. If only one of these methods detected waveforms, that method was prioritized. No output was generated if neither method detected waveforms. Table 2 lists the output methods. The hit and FA rates were calculated for 19 trials, as in the previous experiments. RMS using the AT method was set to the last 2 sec, α was set to 4, and k in the k-NN method was set to 5.

Table.2: Output pattern

| | k-NN ON | k-NN OFF |
|---------------|---------|------------|
| AT method ON | Output | Output |
| AT method OFF | Output | Not Output |

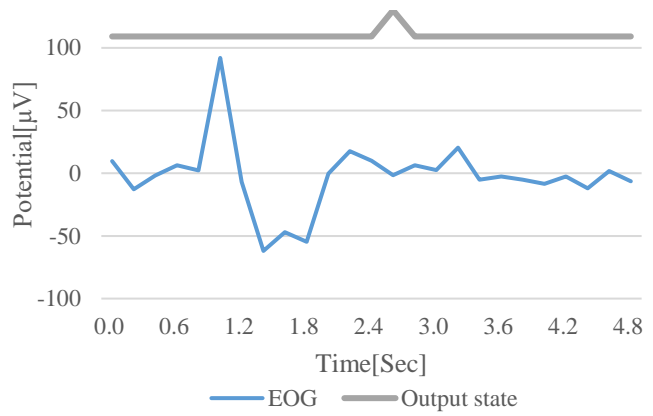


Figure.4: Waveform of a Hit detection using k-NN method

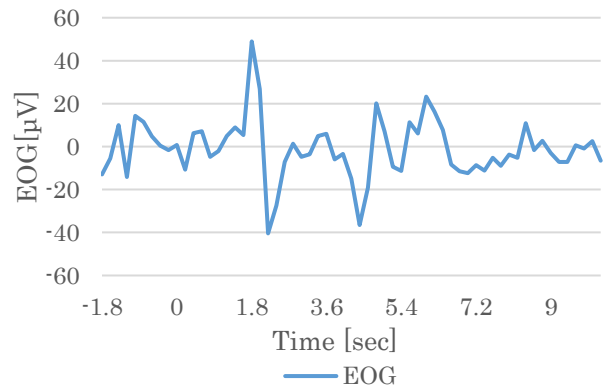


Figure.5: Waveform of a Miss detection using k-NN method

5.2 Result

The average hit and FA rates calculated from the 19 trials were 94% and 9%, respectively (Fig. 6). The average hit rate was highest using both the AT and k-NN methods, suggesting that we can integrate the waveform detection capabilities of both methods. On the other hand, the average FA rate using the two methods was second to that of the AT method. Observing the erroneously detected portion of both methods, only one of them was miss detected. It can be said that erroneous detection is output as is because detection of waveforms is a priority in the current system.

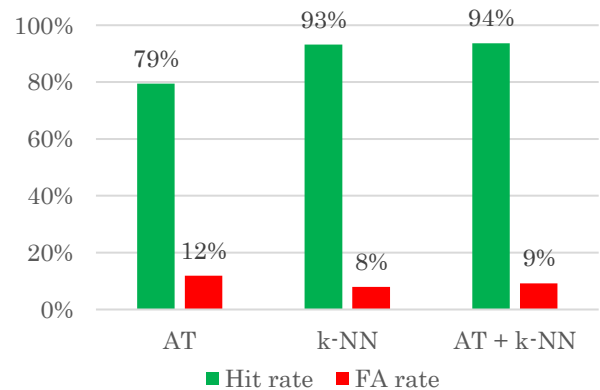


Figure.6: Result of AT method + k-NN method

6. Discussion

The results of the present study indicated that the combined use of the AT and the k-NN methods is capable of displaying both the true- and false-positive waveforms from each method. As described, we currently pick up false positives from both methods. Therefore, we believe that we should combine both methods to prevent erroneous detection. The combined effect has highest value for positive waveform detection. Both the detection rate and speed are important as factors in the interface is used as an input device. The results of Saito's [2] study showed an optional blink detection rate of 98% and those of Dhanush's [3] study showed a rate of 80%. Our method has 93%, which was not much less than that of Saito and greater than that of Dhanush. There is a Brain Computer Interface (BCI) using an electroencephalogram (EEG) based on a biological signal, with an information transfer rate (ITR) as a BCI indicator. ITR is obtained from Eq. 6 based on the option N , detection the rate p , and the input time T .

$$ITR = \left\{ \log_2(N) + p \log_2(p) + (1-p) \log_2 \frac{1-p}{N-1} \right\} \times \frac{60}{T} \text{ [bits/min]} \quad (\text{eq.6})$$

ITR in our method was 22 bits/min ($N = 2, p = 94\%, T = 1.7$ sec). For example, Kitamura's [8] research on the P300 speller for ALS patients showed BCI of 12 bits/min ($N = 60, p = 81\%, T = 21$ sec). In addition, Geng's [9] motor imagery BCI was 16 bits/min ($N = 4, p = 68\%, T = 2$ sec). Our proposed method resulted in a higher ITR than that from either of these methods; therefore, we suggest that the effectiveness of the proposed method in this study could be used as a BCI.

In future studies, measures against erroneous detection could be assessed by combining the two methods and examining a method by which to update the training data from the k-NN method. The purpose of this research was to conduct highly accurate waveform detection without having to prepare the patient in advance; therefore, we believe that the training data should be updated in the early stages of system operation according to current conditions.

7. Conclusion

In the current study, we assessed a method by which to develop a bio-signal interface using biological signals from eye closed-eye potential. From the results of our study, we have proposed a combined method using both the AT and k-NN methods. The result of the combined method showed an average hit rate or 94% and an average FA rate of 9%.

The combined average hit rate was higher than that from the AT and k-NN methods alone. The ITR, an evaluation index, was calculated as 22 bits/min, which was higher than that using other bio-signal interfaces, indicating a better bio-signal interface result. We believe that it is necessary to combine the two methods and investigate any countermeasures for avoiding false detection.

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