EFFICIENT FEATURE FOR THE CLASSIFICATION OF EYE MOVEMENTS USING ELECTROOCULOGRAPHY SIGNALS

by

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Electrooculography (EOG) signal is widely and successfully used to detect activities of human eye. The advantages of the EOG-based interface over other conventional interfaces have been presented in the last two decades; however, due to a lot of information in EOG signals, the extraction of useful features should be done before the classification task. In this study, an efficient feature extracted from two directional EOG signals, vertical and horizontal signals, has been presented and evaluated. There are the maximum peak and valley amplitude values, the maximum peak and valley position values, and slope, which are derived from both vertical and horizontal signals. In the experiments, EOG signals obtained from five healthy subjects with ten directional eye movements were employed: up, down, right, left, up-right, up-left, down-right down-left clockwise and counter clockwise. The mean feature values and their standard deviations have been reported. The difference between the mean values of the proposed feature from different eye movements can be clearly seen. Using the scatter plot, the differences in features can also be clearly observed. Results show that classification accuracy can approach 100% with a simple distinction feature rule. The proposed features can be useful for various advanced human-computer interface applications in future researches.

Key words: *electrooculography signal, eye movement, human-computer interface*

Introduction

Electrooculography (EOG) signal is widely and successfully used to detect activities of human eye. The understanding, characterization, and classification of eye movements based on EOG signals play an important role as fundamental for a human-computer interface (HCI) system. As a result, various HCI systems based on EOG signals have been developed [1-8]. The HCI systems based on EOG signals can be applied to a wide variety of applications. For example, EOG signals were used in the communication support system development for people with disabilities such as amyotrophic lateral sclerosis (ALS) [9]. An electric power wheelchair controlled by EOG signals has also been developed as movement support device [10-12]. Other applications of EOG signals include a virtual keyboard control [13], an eye-writing system [14], and an activity recognition system [3].

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Two important computational steps in HCI systems based on EOG signals are feature extraction and classification. Barea *et al.* [2] proposed the use of continuous wavelet transform and radial-basis-function neural network for the eye movement detection processing system. In addition, the corresponding eye movement detection processing system in eight directions was implemented and validated [15]. Postelnicu *et al.* [16] employed peak amplitudes from EOG signals, a set of fuzzy logic rules and a deterministic finite automation for the development of EOG-based visual navigation interface in six directions. Aungsakul *et al.* [17] proposed fourteen useful features extracted from specific characteristics of two directional EOG signals such as the maximum peak and valley amplitude values (*PAV* and *VAV*), and the maximum peak and valley position values (*PAP* and *VAP*). The analysis-of-variation test resulting from the eye movement detection system in eight directions showed that the differences in mean features between the movements were statistically significant for ten features ($p < 0.0001$) including *PAV*, *VAV*, *PAP*, and *VAP*. In addition, the classification accuracies based on a distinction feature rule from the proposed features approached 100% for three subject testing [18]. However, the number of features used in the algorithm was quite high and the distinction feature rule was quite complicated.

To reduce the number of features used in the algorithm and simplify the distinction feature rule, we propose an efficient feature for HCI systems based on EOG signals in this research work.

Materials and methods

Experimental set-up

Figure 1 shows the placement of five surface electrodes around the eyes. Vertical leads were acquired on the above and below of the right eye (Ch.V+ and Ch.V-). In the vertical direction, two eyes move in conjunction; hence, for the vertical signal, only one right eye was used. Horizontal leads were acquired by two electrodes on the right and the left of the outer canthi (Ch.H+ and Ch.H–). A reference electrode was placed on forehead (G).

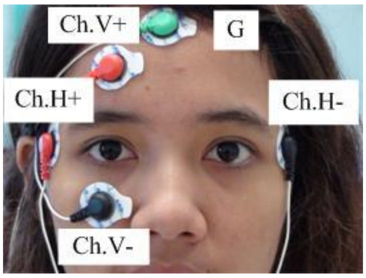


Figure 1. Electrode placement

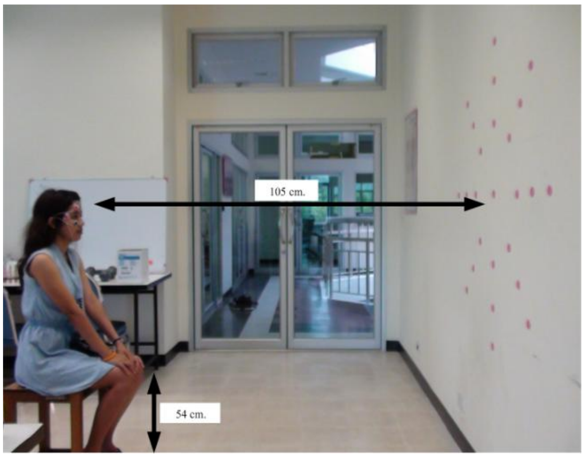


Figure 2. Experimental set-up

Figure 2 shows the experimental set-up for EOG signal acquisitions. The volunteer sat on a chair. The height of the chair is about 54 cm above the floor. The eye targets were placed on the same level of line of sight in the wall at a distance of 105 cm from the volunteer. Figure 3 shows ten positions of eye targets used in EOG signal acquisition. EOG signals from three categories of eye movements consisting of basic, advanced and complicated eye movements were acquired. While the basic eye movements were composed of up, down, right, and left eye movements, the advanced eye movements comprised up-right, up-left, down-right, and down-left eye movements. In addition, the complicated eye movements were clockwise (CW) and counter clockwise (CCW) eye movements.

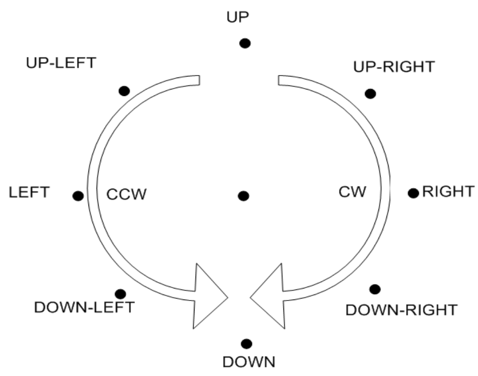


Figure 3. Positions of eye targets

Data acquisition

All EOG signal recordings were carried out using a commercial wireless system (Mobi6-6b, TMS International BV, The Netherlands). A band-pass filter of 0.1-500 Hz bandwidth and an amplifier with 19.5x were set for the recorded system.

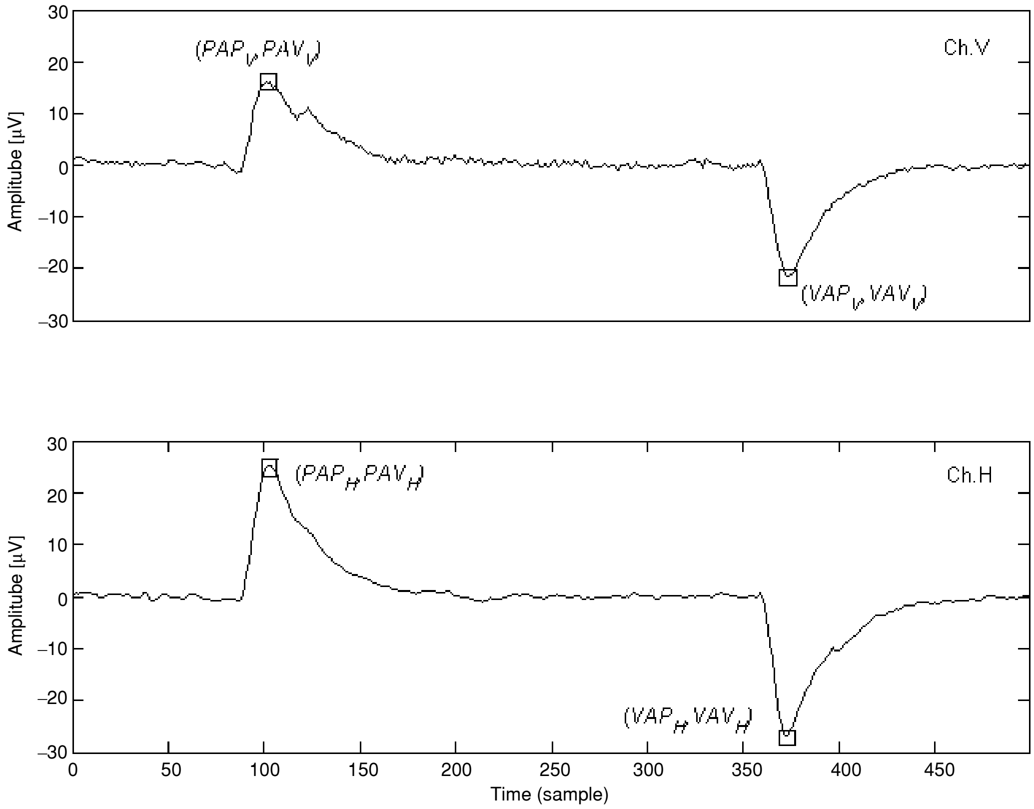


Figure 4. Example of slope feature calculation from up-right eye movement at a sampling rate of 128 Hz; top panel: a slope from vertical signal, bottom panel: a slope from horizontal signal

The sampling rate was set to 1024 Hz. However, the energy frequency bands of the EOG signal are fallen in range of 0.1 to 30 Hz. Thus the sampling rate was reduced to 128 Hz in pre-processing stage. The EOG data were recorded from five normal subjects with ten directional eye movements: up, down, right, left, up-right, up-left, down-right, down-left, CW, and CCW. Each movement was hold for 2 s and was performed 20 times throughout a trial. As a result, 100 datasets from 5 volunteers were obtained from each directional movement.

Feature calculation

We propose an efficient feature based on the slope extracted from two directional EOG signals: vertical and horizontal signals in this paper. On the one hand, the slope from vertical signal can be expressed:

$$M_{\mathrm{V}} = \frac{VAV_{\mathrm{V}} - PAV_{\mathrm{V}}}{VAP_{\mathrm{V}} - PAP_{\mathrm{V}}} \tag{1}$$

where M_{V} is a slope from vertical signal, VAV_{V} is a minimum valley amplitude value from vertical signal, PAV_{V} is a maximum peak amplitude value from vertical signal, VAP_{V} is the position where the minimum valley amplitude value from vertical signal locates, and PAP_{V} is the position where the maximum peak amplitude value from vertical signal locates. On the other hand, the slope from horizontal signal is given by:

$$M_{\mathrm{H}} = \frac{VAV_{\mathrm{H}} - PAV_{\mathrm{H}}}{VAP_{\mathrm{H}} - PAP_{\mathrm{H}}} \tag{2}$$

where M_{H} is a slope from horizontal signal, VAV_{H} is a minimum valley amplitude value from horizontal signal, PAV_{H} is a maximum peak amplitude value from horizontal signal, VAP_{H} is the position where the minimum valley amplitude value from horizontal signal locates, and PAP_{H} is the position where the maximum peak amplitude value from horizontal signal locates. Figure 4 shows an example of slope feature calculation from up-right eye movement.

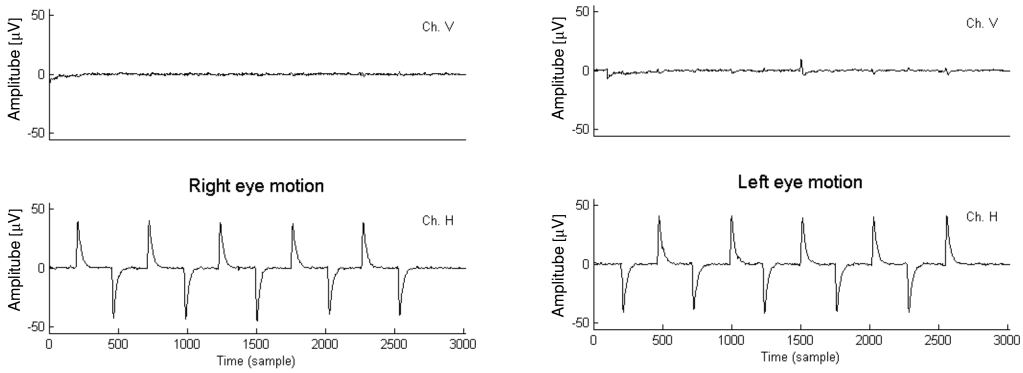
Results and discussion

Signal characteristics

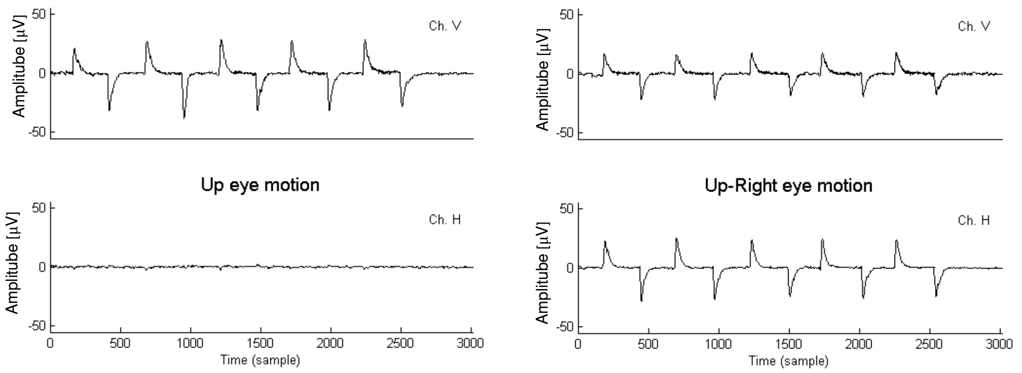
Figure 5 (top row left column) shows the EOG signal from right eye movement. Only the horizontal EOG signal in the bottom panel can be seen because the volunteer only moves the eyes in the horizontal direction. Figure 5 (top row right column) shows the EOG signal from left eye movement. The horizontal EOG signal from the left eye movement is the inversion of that from the right eye movement. Figure 5 (middle row left column) shows the EOG signal from up eye movement resulting in only the vertical EOG signal in the top panel. When the volunteer moves the eyes in the up-right direction, which is the combination of vertical and horizontal eye movements, the vertical and horizontal EOG signals are shown in the top and bottom panels of fig. 5 (middle row right column), respectively. Figure 5 (bottom row left column) shows the EOG signal from clockwise eye movement. More complicated signal characteristics can be seen in both directions. As a comparison, the EOG signal from counter clockwise eye movement is shown in fig. 5 (bottom row right column). While the EOG signals in vertical directions from both movements contain a certain degree of similarity, the EOG signals in horizontal directions have an inversion appearance.

Table 1 shows the slope features determined using vertical and horizontal signals from 10 different eye movements. We can clearly see that 10 different eye movements

Top row



Middle row



Bottom row

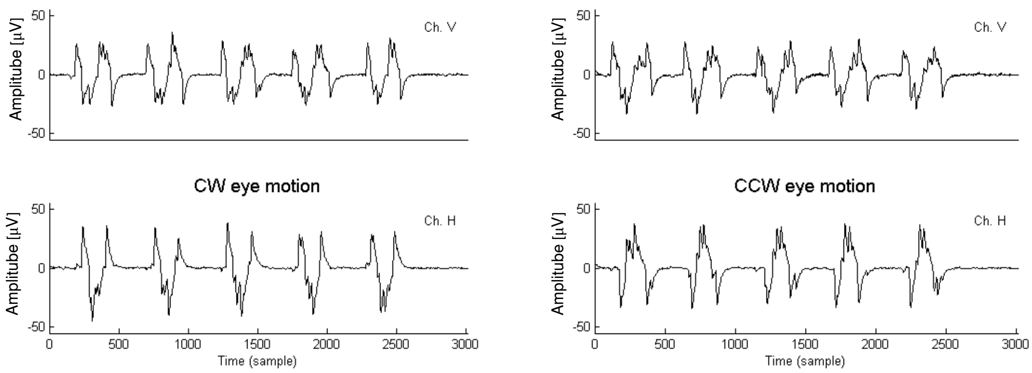
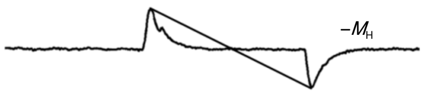
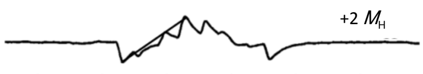


Figure 5. Top row: EOG signals from right (left column) and left (right column) eye movements. Middle row: EOG signals from up (left column) and up-right (right column) eye movements. Bottom row: EOG signals from CW (left column) and CCW (right column) eye movements. All EOG signals were acquired at a sampling rate of 128 Hz.

Table 1. The slope features determined using vertical and horizontal signals from ten different eye movements

Movement	Vertical signal	Horizontal signal
Up	 $-M_V$	 $M_H = 0$
Down	 $+M_V$	 $M_H = 0$
Right	 $M_V = 0$	 $-M_H$
Left	 $M_V = 0$	 $+M_H$
Up-right	 $-M_V$	 $-M_H$
Up-left	 $-M_V$	 $+M_H$
Down-right	 $+M_V$	 $-M_H$
Down-left	 $+M_V$	 $+M_H$
CW	 $-2\ M_V$	 $-2\ M_H$
CCW	 $-2\ M_V$	 $+2\ M_H$

can be efficiently categorized based on the signs and amplitudes of slope features from vertical and horizontal EOG signals.

Statistical characteristics

Figure 6 shows an example of the scatter plot of the slope feature from ten eye movements from a volunteer. While the x-axis of the scatter plot is the slope feature from the horizontal EOG signals of the volunteer, the y-axis of the scatter plot is the slope feature from the vertical EOG signals of the volunteer. We can clearly see the separation of slope features from 10 eye movements without the degree of overlapping. Therefore, the simple classifier such as a decision tree or a simple distinction feature rule can perfectly separate the eye movements with 100% accuracy. As a comparison, figs. 7 and 8 show an example of the scatter plots of the *PAP* and *VAP* features from ten eye movements proposed in [17] and [18], respectively. We can clearly see a certain degree of overlapping resulting in the use of more features and a more complicated distinction feature rule for classifying eye movements.

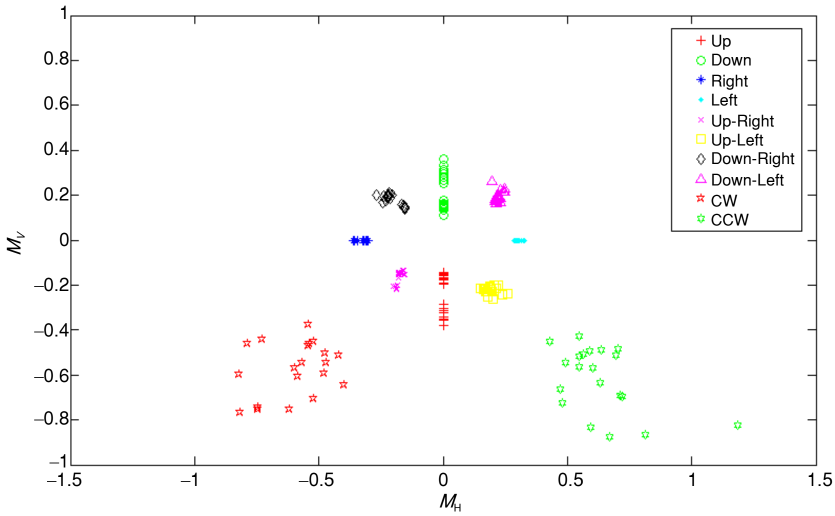


Figure 6. Example of the scatter plot of the slope feature from ten eye movements of a volunteer

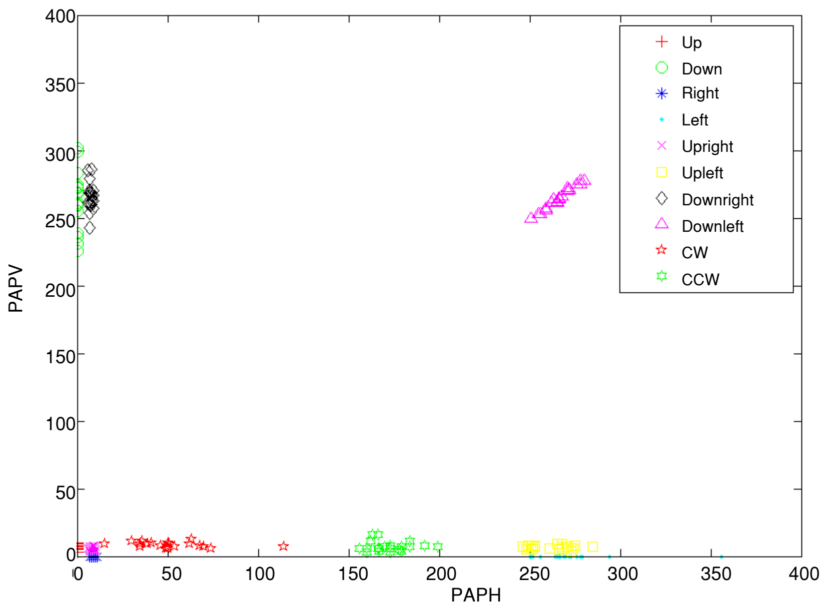


Figure 7. Example of the scatter plot of the *PAP* feature from ten eye movements of a volunteer

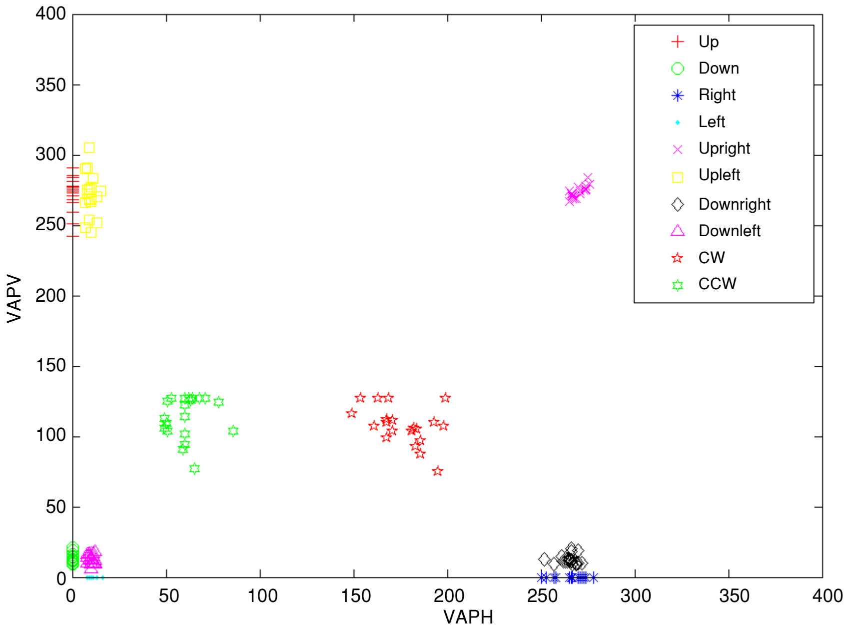


Figure 8. Example of the scatter plot of the VAP feature from ten eye movements of a volunteer

Table 2. Statistical measurement values (mean ± standard deviation and the coefficient of variation, cov) of slope features in vertical and horizontal directions determined from 100 EOG signals of five volunteers for each eye movement.

Eye movement	Vertical signal	Vertical cov	Horizontal signal	Horizontal cov
Up	–0.202±0.044	–0.218	0.000±0.000	N/A
Down	0.208±0.030	0.144	0.000±0.000	N/A
Right	0.000±0.000	N/A	–0.278±0.032	–0.115
Left	0.000±0.000	N/A	0.260±0.028	0.108
Up-right	–0.148±0.020	–0.135	–0.148±0.020	–0.135
Up-left	–0.186±0.022	–0.118	0.176±0.024	0.136
Down-right	0.170±0.022	0.129	–0.194±0.024	–0.124
Down-left	0.178±0.020	0.112	0.170±0.020	0.118
CW	–0.546±0.106	–0.194	–0.576±0.286	–0.497
CCW	–0.532±0.114	–0.214	0.642±0.204	0.318

Table 2 shows the statistical measurement values (mean ± standard deviation and the coefficient of variation, cov) of slope features in vertical and horizontal directions determined from 100 EOG signals of five volunteers for each eye movement. The degree of separation from statistical values agrees with those from the scatter plot of an individual volunteer very well. These results clearly show the confirmation of performance of the proposed slope feature in classifying EOG signals from ten directions of eye movements.

Conclusion

We present an efficient feature for the classification of eye movements using EOG signals. The feature is determined from the slope of minimum and maximum points in EOG signals from vertical and horizontal electrodes. The proposed slope feature was validated with EOG signals from five volunteers. Results show that the proposed slope feature is very efficient. In other words, ten eye movements can be easily classified using a simple distinction feature rule. The potential applications of the proposed feature to a HCI system, including a communication support system development for people with disabilities, an electric power wheelchair controlled by EOG signals, a virtual keyboard, and an activity recognition system, are ongoing research. Results will be reported in the near future.

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