Why Cannot Control Your Smartphones by Thinking? Hands-Free Information Control System Based on EEG

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Abstract Smartphones are the most frequently used devices for acquiring information, but people should operate the smartphones still using hands, even though wearable devices, e.g., Google Glass, are rapidly spreading. Meanwhile, electroencephalogram (EEG) is commonly used for recording brain activity, to translate the brain signals into computer commands; it is widely used for aiding disabled people. EEG has a potential to enable people to control information directly by brain activity. So, why cannot you control smartphones by thinking? EEG can enable people to control information directly. For example, your favorite song can be played without browsing by brain activity, even your smartphone in the pocket; and it can also prevent risks while driving or walking. We have developed a hands-free brain computer interface of practical use for controlling applications based on user intentions and feelings by adopting a wearable EEG device and smartphones.

Keywords Intentions · Feelings · EEG-based information control system

1 Introduction

Brain-computer interface (BCI) technology has a potential to enable disabled people to control external devices such as computers, wheelchairs or virtual environments

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directly by brain activity rather than by physical means. However, disabled people need to wear high restriction headgear for acquiring high-quality EEG based on many standard positions on the surface of the brain. Currently, smartphones and car navigation systems are the most frequently used convenient devices for acquiring information in daily lives of people, especially for disabled people. By accessing various applications or services on smartphones, people can quickly and easily obtain information in a wide variety of situations, but they still use hands, even though wearable devices, e.g., Google Glass [6], Apple Watch [1], are rapidly spreading. For instance, there is considerable concern that using a smartphone while driving makes an accident risk, to the driver and other people on the road, because it distracts the driver, impairs his control of the vehicle, and reduces his awareness of what is happening on the road around him.

So, why cannot you control smartphones by thinking? We considered that EEG has a potential to enable people to control information on smartphones directly by brain activity. In this way, your favorite song can be played without browsing any information on your smartphone, even it is in a pocket. In this research, we aim to develop a hands-free information controllable system based on a smartphone of practical use for controlling applications (apps) or contents (e.g., Websites) on smartphones without browsing anything, but based on human EEG at anytime and anywhere. The system enables users to automatically control information on smartphones by deliberate control and habitual control. The deliberate control indicates that the users control information for their explicit purposes. We define user intentions as user's purposes, that is what the user actually wants to do with an interaction with an app on a smartphone. Therefore, the deliberate control is determined by extracting the users' most frequently used apps in personal from their usage history of smartphones and the user intentions through their EEG states. Then, the system automatically recommends the most frequently used apps by different time periods, they can be automatically controlled on smartphones by the extracted user intentions. The habitual control indicates that the users perform the control same as their usual behavior. In general, feelings are users' emotions; we define user feelings as users' brain states, referring to where and when of their surrounding situation. Then, the system automatically controls the users' habitually-used apps by extracting their feelings and acquiring similar feelings in the past through the EEG states and their situations (i.e., location and time), for example, starting users' habitually-used apps, or playing music according to users' situations.

Although several techniques for voice-based and vision-based methods for hands-free control of devices or software have been studied [3], these studies have focused on the hands-free feature; they do not solve the aforementioned issues on information control on smartphones. To achieve our goal, we utilize EEG instead of hands. B-Bridge developed a wearable EEG measurement device, called B3 Band [2], it is a low restrain headband equipment at a low price that are good for health care for disabled people. As depicted in Fig. 1, our novel EEG-based information controllable system makes two primary research contributions:

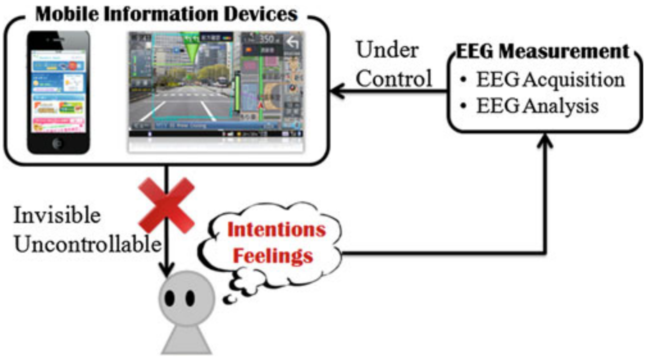

Fig. 1 Proposed EEG-based information control system

1. Users can automatically control apps on smartphones by extracting user intentions through voice guidance. It is possible to measure EEG states with a simple EEG measurement device (only 3 electrodes) and smartphones.
2. Users can automatically control their habitually-used apps by extracting their current feelings that are similar to the past feelings. In order to extract users' feelings by acquiring spatio-temporal information, the system measures EEG states that are affected by the surrounding situations of them.

For example, a user is frustrated in a traffic jam, when he drives a car on the road. Our system extracts his feeling and assumes he is in the traffic jam by measuring his EEG, and compares the past similar feelings by acquiring situations of him. Therefore, it enables playing a music to soften his feeling, since he habitually plays the music in the same situation. Specially, our system can learn EEG features of disabled people, to help them automatically control their purposes about what they want to do according to their surrounding situations.

2 System Overview and Related Work

2.1 System Overview

As depicted in Fig. 2, we propose two methods to control apps or contents of smartphones based on human EEG. In the system, we connect the smartphone to a simple EEG device via a Bluetooth. EEG data are acquired by the smartphone. As an initial learning of users' brain states in advance, the system measures their EEG under a concentration or relaxation state. Then, we developed a classifier by the initial learning that is stored in a server.

In order to control all apps (e.g., mails, SNS) or contents on smartphones by extracting user intentions, they are firstly announced by voice guidance to users.

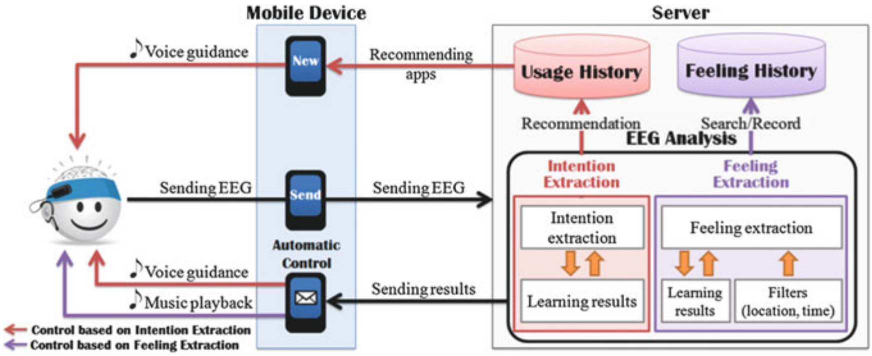

Fig. 2 System configuration diagram

Next, users express their intentions (thought) to the announced information from EEG with two states, i.e., concentration and relaxation; then, our system measures and learns their EEG under these states. The measured EEG data is sent to the server through the smartphone. In the server side, the system inputs the received EEG into a classifier to determine the EEG states. Then, the system automatically controls apps or contents on smartphones, according to the determined results, and announces the results to the users by voice guidance.

In order to control apps or the contents on smartphones in the same situations as before by extracting user feeling, our system acquires users' locations and time information in advance, to measure the EEG that is affected by situations of the users and to search for the similar EEG in the past. Furthermore, the acquired location, time information and the controlled histories are stored in a database, called a feeling history. Next, the measured EEG data is sent to a server through the smartphone. In the server side, the system accesses the feeling history database, and searches for the similar EEG data in the past, then, the system controls apps through his EEG when he is in the same situations.

2.2 Related Work

Several techniques of hands-free control system have been studied. VoiceBot [7] is a voice controlled robotic arm, using the Vocal Joystick inference engine. This study based on voice controls needs high-quality speech recognition techniques, which is not suitable for outdoor use, since a lot of outside noise may affect the quality of the voice. In this work, we aim to develop a hands-free information control system to recommend users' required information according to their surrounding situations by measuring EEG states.

Lampe et al. [9] presented an Internet-based brain-computer interface (BCI) for controlling an intelligent robotic device with autonomous reinforcement-learning.

EEG-based brain-controlled wheelchair has been developed for use by completely paralyzed patients [12]. The proposed design includes a novel approach for selecting optimal electrode positions, a series of signal processing algorithms and an interface to a powered wheelchair. These studies have focused on hands-free device control for patients, and they measured brain activity by using high price and high restrain equipments e.g., headgear and MRI (magnetic resonance imaging), at homes or hospitals. In this work, we use a simple headband type EEG measurement device for not only patients, but also general users to automatically control apps or the contents on smartphones.

3 EEG Measurement

We aim to develop a hands-free information controllable system for operating apps or the contents on smartphones without using hands. For this, the system was designed to extract user intentions and feelings by measuring EEG data.

3.1 Classifier Configuration

We developed an application of EEG measurement on smartphones to acquire a sample learning data for each individual user in advance. We adopted a simple EEG measurement device, B3 Band (see Fig. 4a). The application first makes a connection between the smartphones and the B3 Band via a Bluetooth. Then, all the EEG data can be measured and sent to the server. The processing flow is shown in Fig. 3, (a) Explaining how to measure EEG in 7 s. (b) Selecting CONNECT button to connect the B3 Band with a Bluetooth. (c) Starting a task by START button. (d) Indicating a user's state, i.e., concentration or relaxation.

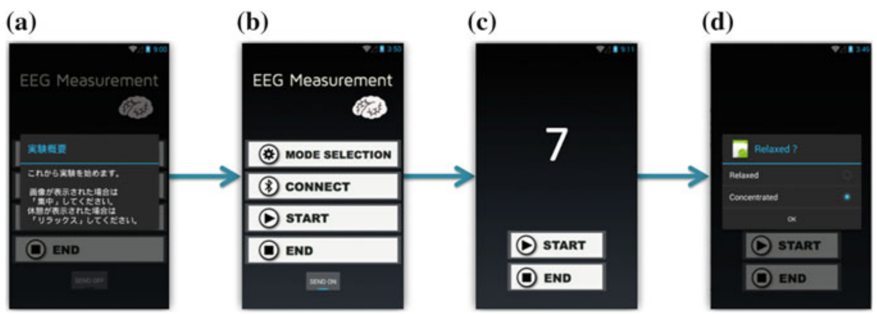

Fig. 3 Screenshot of processing flow of our application

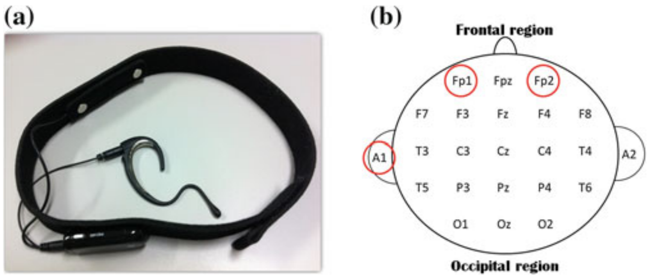

Fig. 4 B-Bridge B3 Band and electrode placements

3.2 *Simple EEG Measurement Device*

Electric potentials were recorded from the scalp surface by an EEG measurement device; it mainly reflects postsynaptic potentials that occurred in dendritic spines of pyramidal neurons of the cerebral cortex. Figure 4b shows electrode placements for the International 10–20 Standard [8]. Since eye-blink affects EEG during measurement [11], we adopted an algorithm by B3 Band, which enabled to identify and remove artifacts, i.e., signals caused by eye blinks and ocular movements. The size of the B3 Band is 54 mm(L) × 25 mm(W) × 17 mm(H), the weight of it about 100 g. It is a compact, low restraint device. The metal part of the left ear in the B3 Band corresponds to A1 location, and electrodes are mounted on the band part which corresponded to Fp1 and Fp2 locations. Eight indicators of EEG are considered to be correlated with the user's states, e.g., levels of alertness and relaxation. EEG powers of eight frequency bands are believed to be correlated with the mental state, e.g., levels of alertness and relaxation. Degrees of Attention (concentration) and Mediation (relaxation) are calculated, which can be acquired once per second by taking a value of $0 \sim 100$.

4 Analysis of EEG Data

In order to extract user thoughts or behaviors, we used two analysis methods. One is analyzing user thought or behavior patterns by using Support Vector Machine (SVM), the other one is determining brain states by taking a threshold value of the similarity of EEG are calculated by cosine similarity. The threshold value is decided by using Half Total Error Rate (HTER). We also extended these two methods to v-SVM (voting-SVM) and v-HTER (voting-HTER).

4.1 SVM-Based Analysis

Since the generalization capability of SVM is high in class determination [5], we then use it to determine concentration and relaxation states of users with two manners. One is SVM that used EEG indices (Attention and Meditation) per second as inputs into a classifier, which are acquired by a simple EEG device. The other one is o-SVM (order-SVM) that used EEG indices per user's thought time as inputs into a classifier. Outputs of them are concentration and relaxation states. If acquired EEG data are unknown data, its states are determined by using a classifier. Else if acquired EEG data are known learning data, its states are determined by using cross-validation. The determination of the acquired EEG data by using the classifier per second is described as follows:

$$\begin{cases} concentration \ if \ y_1 > y_2 \\ relaxation \qquad else \end{cases}$$

Here, the output value of concentration is y_1, the output value of relaxation is y_2, both of them take the real value of $0 \sim 1$.

4.2 HTER-Based Analysis

Chuang et al. [4] proposed an authentication method based on EEG, and confirmed that it has high accuracy. We then used this method to determine concentration and relaxation states of users. Therefore, we first calculate the cosine similarity of each EEG data and its center of gravity, and determine a temporary threshold value by multiple cosine similarities. Each temporary threshold value is calculated by error rate, and the temporary threshold value with the minimum error rate of a classifier is chosen. EEG states are determined by using a group of EEG when users are concentrated or relaxed as follows:

1. Calculating a center of gravity coordinate g_C (g_R) of a group of concentrated (relaxed) EEG by Eq. (1).

$$g_{C(R)} = \left(\frac{\sum_{i=1}^{k} a_i}{k}, \frac{\sum_{i=1}^{k} m_i}{k} \right) \tag{1}$$

   Here, k denotes each data in a group of concentrated (relaxed) EEG. a_i is a value of Attention, and m_i is a value of Meditation.

2. Calculating a cosine similarity of each data $d(k, C)$ ($d(k, R)$) in a concentration (relaxation) group and its g_C (g_R) by Eq. (2).

$$\cos(g_{C(R)}, d(k, C(R))) = \frac{g_{C(R)} \cdot d(k, C(R))}{|g_{C(R)}||d(k, C(R))|} \tag{2}$$

3. Assuming a threshold value Th_{Ck} (Th_{Rk}) of each k of cosine similarity from 2., and the cosine similarity of each data and each center of gravity coordinate is determined by a temporary threshold. The determined results are measured in terms of their *False Acceptance Rate* (FAR_{Ck} or FAR_{Rk}) and *False Rejection Rate* (FRR_{Ck} or FRR_{Rk}).

$$FAR_{Ck(Rk)} = \frac{\#\text{incorrect data are determined as correct}}{\text{Total number of incorrect data}}$$

$$FRR_{Ck(Rk)} = \frac{\#\text{correct data are determined as incorrect}}{\text{Total number of correct data}}$$

4. Calculating the average $HTER_{Ck}$ ($HTER_{Rk}$) of FAR_{Ck} and FRR_{Ck} (FAR_{Rk} and FRR_{Rk}) from 3. by Eq. (3), and the minimum of error rate $HTER_{Ck}$ ($HTER_{Rk}$) as a threshold value $Th2_C$ ($Th2_R$) is decided in a concentration (relaxation) group.

$$HTER_{Ck(Rk)} = \frac{FAR_{Ck(Rk)} + FRR_{Ck(Rk)}}{2} \tag{3}$$

5. Calculating the cosine similarity of measurement data, g_C (g_R) of the concentration (relaxation) group, and a concentration (relaxation) state to be determined if the cosine similarity is more than the decided $Th2_C$ ($Th2_R$) from 4. Here, a threshold value with a low error ratio.

4.3 SVM and HTER Based on Voting Principle

We newly propose a determination method that is based on voting of multiple EEG states by taking a majority decision in whole thought time after determining the EEG state per second. v-SVM utilized voting of the determined results of SVM in one second, and v-HTER utilized voting of the determined results of HTER in one second. The procedure of them is described as follows:

1. We determined EEG states by SVM or HTER in one second.
2. We re-determined the results by using the results from the whole thought time, when the determined number of concentration or relaxation states is max and the voting rate is more than a threshold value Th_v from 1.

5 Evaluation

The purpose of this evaluation was to verify whether our proposed user intention extraction method was useful for helping users to control apps or the contents on smartphones based on their EEG. 7 college students (4 males, 3 females) completed all experiments in a general environment without substantial noisy.

5.1 User Intention Extraction Based on Voice Guidance

We first conducted an experiment to evaluate the performance of our proposed intention extraction method in a condition of voice guidance. In this experiment, our developed EEG measurement application notified information to users by means of voice guidance, and the users did not browse any information on smartphones. There are 6 steps of this experiment as follows:

1. Presenting background images, and running voice guidance
2. Measuring the subjects' EEG for 7 s after voice guidance
3. Extracting EEG for 5 s ($2 \sim 6$) out of the 7 s measurement
4. Labeling the EEG state into concentration or relaxation
5. Determining EEG state per second by using SVM and HTER
6. Re-determining the results of 6. By voting

A black picture was used in order to make no differences for ease of concentration and relaxation. Our developed application provided three kinds of voice guidance, *Do you want to see emails?*, *Do you want to play music?*, and *Do you want to search Web pages?*. All subjects participated in this experiment. In one set of measurement, voice guidance was played 3 times. Then, we acquired 15 EEG data ($= 5\,\text{s} \times 3$) in one set. We measured a total of 300 EEG data (concentration: 150, relaxation: 150) in twenty sets. Table 1 shows the classification results.

We also used scenery pictures were shown in Fig. 5, since our assumed environment was not only indoor but various outdoor situations. Although a sound is necessary in a real environment, it may introduce unwanted noise into the EEG. Therefore, we only presented scenery pictures to subjects in this experiment as a first step for the study. 4 subjects (*A*, *B*, *C*, *D*; males) participated in this experiment. In one set of measurement, voice guidance was played 3 times, and background images were presented 4 times. Therefore, we acquired 60 EEG data ($=5\,\text{s} \times 3 \times 4$) in one set. We measured a total of 360 EEG data (concentration: 180, relaxation: 180) in six sets. Table 2 shows the classification results by each determination method, and the results can be summarized as follows:

- The accuracy rates of v-SVM in all subjects with a black picture and scenery pictures were higher than those of SVM. The results suggest that v-SVM is useful for improving the accuracy rates.

Fig. 5 Examples of scenery pictures

Table 1 Results of intention extraction by presenting a black picture

Subject	SVM (%)	o-SVM (%)	v-SVM (%)	HTER (%)	v-HTER (%)
A	61.0	60.0	**68.3**	60.0	66.7
B	63.3	61.7	**73.3**	59.7	58.3
C	64.0	68.3	**71.7**	63.0	65.0
D	70.0	73.3	**85.0**	63.0	66.7
E	54.0	53.3	**63.3**	60.3	60.0
F	64.7	68.3	**76.7**	61.7	66.7
G	61.0	63.3	**75.0**	66.3	65.0
Average	64.8	64.1	**74.6**	61.4	64.8

Table 2 Results of intention extraction by presenting scenery pictures

Subject (%)	SVM (%)	o-SVM (%)	v-SVM (%)	HTER (%)	v-HTER (%)
A	61.1	56.9	**66.7**	50.0	50.0
B	69.7	70.8	**88.9**	60.0	58.3
C	65.8	63.9	**79.2**	57.2	58.3
D	62.5	61.1	**72.2**	57.2	54.2
Average	64.8	63.2	**76.7**	56.1	55.2

- The accuracy rates of *A* and *D* were higher for the black picture, and those of *B* and *C* were higher for the scenery pictures. This may indicate that the black picture could easily make *A* and *D* concentrated and relaxed, and the scenery pictures could easily make *B* and *C* concentrated and relaxed.
- Compared average accuracy rates of HTER and SVM with a black picture and scenery pictures, the average accuracy rate of HTER was lower than that of SVM. Because we determined the threshold that is corresponded to all data including noise data.

This experiment indicated that our method can identify which picture easily makes the subjects concentrated and relaxed. Our method still has a problem about the determination of the threshold for HTER. Therefore, we conducted the following experiments without the methods using HTER.

5.2 User Intention Extraction Based on Mental Arithmetic

We confirmed that our method was able to extract user intentions by measuring concentration and relaxation states from EEG in previous experiments. In order to realize concentration and relaxation states of subjects, Mizuhara et al. [10] combined simultaneous fMRI (functional magnetic resonance imaging) and EEG measurements

Table 3 Results of intention extraction while walking and standing

Subject	While walking		While standing	
	SVM (%)	v-SVM (%)	SVM (%)	v-SVM (%)
A	80.0	**100.0**	71.7	**91.7**
C	61.7	**75.0**	71.7	**91.7**
G	70.0	**100.0**	83.0	**100.0**
Average	70.6	**91.7**	75.7	**94.5**

during a mental arithmetic task. Since beta synchronization was related to the concentration state, in this experiment, we evaluated user intention extraction during the mental arithmetic task that may easily make users concentrated. For this experiment, there are 4 steps under the eyes closed.

1. Ringing a mental arithmetic start sound
2. Measuring the subjects' EEG (concentration state) for 7 s in a mental arithmetic task (serial subtraction of a random constant from 1000)
3. Ringing a mental arithmetic end sound
4. Measuring the subjects' EEG (relaxation state) for 7 s in a break

In order to verify whether our system can control information at anytime and anywhere. We evaluated our proposed user intention extraction method during a mental arithmetic task while subjects are walking and standing, and compared the accuracy rates across these conditions. Subjects (*A*, *C*; males, *G*; female) participated in this experiment. We extracted only 5 s of EEG from 7 s, and we acquired 10 EEG data (=5 s $\times$ 2) in one set. We measured a total of 60 EEG data (concentration: 30, relaxation: 30) in six sets. Measurement environment for *A* and *C* was quiet and less crowded indoor and *G* was quiet and less crowded outdoor.

The experimental results are shown in Table 3. Compared the average accuracy rates of SVM and v-SVM in all subjects between the conditions of walking and standing, the accuracy rate for standing was higher in all subjects, and the results suggest that it is difficult for subjects to control their EEG in the mental arithmetic task while they were moving (e.g., walking).

6 Conclusion and Future Work

In this paper, we developed a novel EEG-based automatic control system for controlling all apps and the contents on smartphones without hands. The experimental results shown that the system has a potential to automatically control information on smartphones by the user intentions from the EEG states.

For future work, we plan to enhance the system based on the experimental results, and the experiments should be carried out in many situations (e.g., driving) with many more subjects of different age groups.

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