EEG-based Brain-computer Interface for Smart Living Environmental Auto-adjustment

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Abstract

An EEG-based smart living environmental control system to auto-adjust the living environment is proposed in this study. Many environmental control systems have been proposed to improve human life quality in recent years. However, there is little research focused on environment control by using a human’s physiological state directly. Even though some studies have proposed brain computer interface-based (BCI-based) environmental control systems, most of them encountered signal quality decline during long-term physiological monitoring with conventional wet electrodes. Moreover, such BCI-based environmental control systems are actively controlled by users; less close-loop feedback capability can be provided between environment and user for automation. Based on the advance of our technique for BCI and the improvement of micro-electro-mechanical-system-based (MEMS-based) dry electrode sensors, we combined these techniques to demonstrate an auto-adjustable living environment control system, e.g., illumination of light and fan speed of air conditioner, depends on the physiological change of the user, even for long-term physiological monitoring. The system is structured with five units: a wireless portable EEG acquisition circuit unit, an interactive flow control unit with a real-time physiology signal processing unit, which is implemented on a dual-core processor, an environment controller unit and a host system for data storage and display. The proposed system has been verified in a simulated environment and the experimental results show that the air conditioner and the lights can be successfully and automatically adjusted in real-time based on the subject’s physiological changes, which indicate the proposed system can be implemented and constructed in the practical smart living environment or for other applications.

Keywords: Electroencephalogram (EEG), Brain computer interface (BCI), Micro-electro-mechanical-system (MEMS)

1. Introduction

Population aging is a worldwide phenomenon [1]. The World Health Organization (WHO) has reported that there will be 1.2 billion people aged 60 and over by 2025 [2]. According to a projection made by the Council for Economic Planning in 2004, the number of people over 65 years will increase to 10% of the total population by 2011; furthermore, people over 75 years will amount to 43% of the population over 65. Although longevity is generally regarded as both a personal privilege and a medical achievement, extended average life expectancy and the resultant rapid increases in old and very old populations still represent a challenge to our society, particularly in terms of the cost of healthcare.

In addition, the relation link between health care cost and national economy is inseparable and undeniable. The statistical data and prediction show that government health care spending is increasing year by year to dominate national gross domestic product (GDP) in the next couple decades [3]. Clinical perspectives evidenced that good sleep duration and habit can enhance human’s immunity to prevent them from such diseases [4-6]. A good sleeping environment, such as with soft illumination of light, comfortable air flow of space and classical music, will help humans sleep well, and can therefore enhance their immunity to prevent kinds of diseases related with lack of sleep [4-6].

There have been many environment control systems proposed and developed [7-11], however most of these systems employed radio frequency identification (RFID), external sensors modules and voice recognition as the controlled signals. Chaya et al. [9] presented a voice-controlled smart house to control devices with voice recognition techniques. Corcoran et al. [10] proposed an universal plug and play
(UPnP) home network infrastructure to provide services to users of a wireless home network from their personal digital assistant (PDA), mobile phone, or a wearable appliance. Users could send out service requests to their home server either with voice or user interface, which overcame the inconvenience of pre-defined areas and pre-recorded voice commands in [9]. Hwang et al. [11] introduced an RFID-based multi-user access control algorithm in a UPnP smart home. Users were asked to take an RFID tag, and many additional RFID readers needed to be installed in different areas in advance for automatic detection of users’ moving into or out of a specific region. Helal et al. [7] and Liu et al. [8] proposed a wear-less smart floor technology with pressure sensors to detect inhabitant location in a house.

However, few studies have focused on environment control by using a human’s physiological state directly, and these systems will not work for users with voice/vision impairment or motion disability. Moreover, even though some brain computer interface-based (BCI-based) devices were proposed and applied for people with disability [12-15], they still had some disadvantages. Gao et al. [12] used steady-state visual evoked potential (SSVEP) to control environmental devices, such as TV, video tape recorders, or air-conditioners. Fast Fourier transform (FFT) and feature extractions were applied in digital signal processor (DSP) to control the electric apparatus. Eibling et al. [13] developed a portable pocket PC-based BCI system. Whitchurch et al. [14] developed a wireless EEG system for long-term monitoring of absent epilepsy patients; the wireless monitoring system was used to enable the physician to monitor the patients’ physiological signals. The popular module, Bluetooth, is approved to apply its transmission band (2.4 GHz) in hospital. Obeid et al. [15] proposed a telemetry system for single-unit recording.

Hence, real-time signal processing function integrated with wireless transmission has become a trend for developing diagnosis or homecare systems because it provides a platform to build sensing and inexpensive BCI systems. However, most systems mentioned above mainly focused on the monitoring function but not on real-time analysis [16], and are actively controlled by users without a close-loop feedback capability between environment and user for automation. Furthermore, these devices also encounter the signal integrity issue for long-term physiological monitoring. Here, the conventional EEG electrodes are most frequently used, but have some drawbacks such as the requirement of conduction gels and abrasion of skin that are time-consuming and inconvenient for users. They are also inappropriate for long-term EEG measurement because EEG signal quality may degrade over an extensive measurement time, caused by the hardened conduction gel. Hence, how to implementing an EEG-based BCI environment control system with automation capability for long-term physiological monitoring in daily life is highly desirable. In our past studies [17,18], micro-electro-mechanical-system-based (MEMS-based) dry electrodes were designed and fabricated to take the place of traditional wet electrodes, with ability to acquire real-time EEG signals for the operational workplaces without requiring conductive paste or scalp preparation in this BCI application. Experiments also showed MEMS-based dry electrodes had low contact impedance with small variance to maintain a consistent signal quality during long-term physiological monitoring, and the performance on hairy skin was nearly as good as that on hairless skin [17]. With the advance of our BCI techniques [19-22], real-time drowsy detection algorithms [23-28], and MEMS-based dry electrode sensors [17,18], we can integrate these techniques and apply them to construct an EEG-based auto-adjustable living environment control system, e.g., illumination of light and fan speed of air-conditioner depends on the physiological signal changes of a user for long-term monitoring in daily life.

Therefore, our goal of this study was to develop a portable, cost-effective and real-time wireless EEG-based BCI smart living environmental auto-adjustment control system. To demonstrate this EEG-based BCI smart living environmental auto-adjustment system, we simulated a small demo environment with two DC fans and three LEDs to evaluate the air-conditioner and lights in the real world. Control signals for fans and LEDs were dependent on the physiological state – alertness, slight drowsiness, and extreme drowsiness – which was analyzed and detected by the system.

2. System architecture

The system architecture in this study is similar with that of our previous research [20]. The major difference between the reference [20] and this study is that we have successfully developed a wireless portable BCI and employed principle component analysis (PCA) technique to detect a driver’s drowsiness in real time. The wireless transmission module employed in [20] is radio frequency (RF) with half-duplex communication, which is not allowed for use in hospital and is rarely implemented on portable devices such as PC, PDA and mobile phone. Based on the experience of system construction in [20], we developed on-board printed circuit boards (PCB) antenna for Bluetooth, which is an allowed full-duplex wireless communication in hospital and is popularly supported by many portable devices. Furthermore, the on-line independent component analysis (ICA), which was proven an effective technique to remove various types of inevitable EEG artifacts, but was most performed offline on a personal computer, was implemented in the embedded signal processing unit for the physiological state estimation.

As shown in Fig. 1, the block diagram of the developed EEG-based BCI smart living environmental control system includes five units: (1) wireless EEG acquisition circuit unit, (2) interactive flow control unit, (3) real-time physiological signal processing unit, (4) environment controller unit, and (5) monitoring host system for DSP development, data storage and status watchdog. The three-layer sensing module in our previous developed BCI system for real-time driver drowsiness detection and warning [20] was re-designed and implemented with two stackable PCBs to reduce PCB size in this system. Such Lego-like design can also improve the hardware flexibility for
future applications. The complex programmable logic device (CPLD) module, which is designed and implemented to control the data flow and format exchange between A/D converter and wireless module, is implemented as the downside PCB, while the analog acquisition module and Bluetooth module are integrated as the upside PCB. The new sensing module can therefore provide 4-channel biomedical signal acquisition, amplification, data flow control and wireless transmission functions. For wireless transmission module, the RF3100 in our previous research [20] can be also used in this sensing module. The size of the sensing module is 4.5 cm × 6.5 cm, and the weight of the module with a Li-ion battery is less than 39 g. The sensing module (including signal acquisition, amplification and wireless units) was designed to operate at 400 mA with 3.7-V DC power supply, and its power consumption is about 1.11 W. The module can be operated continuously for more than 45 hours with a commercial 16,000-mAh Li-ion battery. Also, the embedded signal processing platform (OMAP1510) and the PC host system are powered by AC.

2.1 Wireless EEG acquisition circuit unit

As shown in Fig. 2, the detailed architecture of the wireless EEG acquisition circuit unit consists of two major modules: (1) a signal acquisition and amplification unit that includes MEMS EEG signal acquisition sensors, amplifier and filters, and (2) a wireless data transmission unit that includes an A/D converter and CPLD, that is designed and implemented for data flow control and format exchange between the A/D converter and the wireless data transmission module.

![Figure 1. System architecture of the proposed BCI system. (a) Wireless EEG acquisition circuit unit that includes two stackable PCBs. (a1) One downside PCB, (a2) CPLD digital controller and one upside PCB, (a3) Bluetooth module and (a4) analog acquisition module. (b) Interactive flow control unit. (c) Real-time physiological signal processing unit. (d) Environment controller unit. (e) Monitoring host system for data storage and status watchdog.](image1)

![Figure 2. Detailed architecture of wireless EEG acquisition circuit unit. (a) Signal acquisition and amplification unit, such as MEMS EEG signal acquisition, amplifier, filters. (b) Wireless data transmission unit, such as 8-bit A/D converter and CPLD for data flow control and format exchange between A/D converter and wireless transmission module.](image2)
the artifacts, as shown in Fig. 2(a). The EEG amplifying circuit consists of a differential pre-amplifier with a gain of 99, an isolated amplifier to protect the subject, a band-pass filter that is composed of a low-pass filter and a high-pass filter to preserve 1-100 Hz signals, a differential amplifier with a gain of 51, and a 60-Hz notch filter to eliminate power line noise. The capacitors in the band-pass filter can also compensate the DC-offset. The sensing module carried by the subject is designed to operate with a 3.7-V DC power supply.

2.1.2 Wireless data transmission unit

Figure 2(b) shows the wireless data transmission unit that includes 8-b A/D converters (parallel output, sampling rate = 768 Hz, AD-7575, Analog Device, Inc.), a CPLD (ALTERA FLEX10K EPM 7128STC100-7), and wireless modules. The preprocessed analog EEG signals after 60-Hz notch filter in Fig. 2(a) were first converted to digital, and then transmitted through the wireless modules. The CPLD is designed to control the A/D converter and encode the data for the wireless modules. Two different transmission approaches, RF3100/RF3105 (Ancher Technology, Inc.) and Bluetooth, were both available in this study. The transmission rate is set as 19,200 b/s only in our final design to prevent transmission error, and it can still provide 295 Hz sampling rate for 4-channel signal transmission.

2.2 Embedded signal processing unit

Figure 3 shows the detailed architecture of the embedded signal processing unit composed of two portions: (a) an interactive flow control unit that includes EEG data recovery, data flow control, task management, peripheral control and network control; (b) a real-time physiological signal processing unit that includes down-sampling, Hanning window multiplier, short-time FFT, normalization, moving average, ICA decomposition and drowsy state estimator etc.

Portable biomedical devices are expected to support enhanced capabilities, such as real-time interaction with users, in addition to the online status monitoring and watchdog. Therefore, more complex processing approaches have been proposed for physiological signal analysis, and they will introduce more impacts if it can be implemented in a real device or product. A high-performance signal processing module is adopted and implemented to be the EEG signal processing platform because of its powerful computation capability. Both portions of this embedded signal processing unit are implemented on the OMAP-1510 (Texas Instruments Inc.), the ARM based dual-core DSP processor.

The EEG data acquisition and EEG data signal processing, as shown in Figs. 2 and 3 respectively, are processed at the same time. The EEG data processing procedures in OMAP1510 are illustrated as follows: (1) After receiving EEG data from wireless device, Task A recovers EEG data, and then stores the data in the memory unit. (2) After EEG data is stored, Task B enables the DSP core for data processing. (3) After the DSP core receives the EEG data from the memory unit, data processing flow in Fig. 3(b) is enabled and processed, i.e., down-sampling, Hanning Window multiplier, short-time FFT, moving average and ICA analysis [23,24] are processed. (4) After completing EEG analysis, Task C sends the estimated physiological state back to the memory unit. (5) According the different physiological state, Task D sends out the corresponding command to the network with a TCP/IP envelope.

2.2.1 Multi-task management

Since the proposed BCI system is designed to work in real time, the signal-receiving task should continue when the EEG signal is going through process. An embedded task management algorithm, also called the multi-task scheduling mechanism, is well defined to manage these tasks and to ensure the accurate sampling rate for EEG signal acquisition and data process/ analysis are in real time. The tasks are divided into four types according to their execution period: (1) Task A – wireless device and data recovery control; (2) Task B – call DSP task and transmit EEG data to memory unit; (3) Task C – receiving data from memory unit for further processing in Fig. 3(b), and (4) Task D – Network control and send command with TCP/IP envelope. The time series diagram of the multi-task scheduling mechanism is illustrated in Fig. 4.

Figure 3. Detailed architecture of embedded signal processing unit that is implemented on the OMAP1510 platform. (a) Interactive flow control unit that includes EEG data recovery, data flow control, task management, peripheral control and TCP/IP. (b) Real-time physiological signal processing unit that includes down-sampling, Hanning window multiplier, short-time FFT, normalization, moving average, ICA decomposition and drowsy state estimator, etc.

Figure 4. Time series diagram of multi-task scheduling mechanism.

2.2.2 Real-time signal processing

The EEG signals are acquired at a higher sampling rate to preserve the original signal quality as well as possible for
physiological state estimation. Therefore, a down-sampling to 64-Hz process is applied in the EEG signal analysis to decrease the calculation loading. This sample rate is still quite sufficient for EEG signal analysis because studies [21,25,26,29,30] have shown that the EEG signals’ power spectra of drowsiness are significantly meaningful in the range of 1 Hz to 25 Hz.

The overall procedures for real-time signal processing [23,31,32] in the embedded signal processing unit are described as follows: The received EEG signals are firstly down-sampled to 64 Hz to reduce the calculation loading of the embedded system. After the first 5-second (320 points) EEG data is collected, the input to embedded signal processing unit will be then updated every 2 seconds (128 points). So there will be 3-second (192 points) EEG data overlapped, which will be used for on-line ICA decomposition. The decomposed independent components (ICs) with largest and smallest variance are excluded in this study for spectral analysis [32]. The selected 192-point ICs are multiplied with a 192-point Hanning window to smooth the signals with a 64-point overlap for power spectra analysis. The short-time Fourier transform (STFFT) is used to extract the time-frequency characteristics of the selected ICs. The windowed 192-point ICs are divided into several 32-point frames using the Hanning window again with a moving step size of 8 points. Each 32-point frame is extended to 64 points by zero padding for a 64-point FFT to calculate the power spectra. A 90-second window with 2-second moving step filter is finally used to further minimize the presence of artifacts in the ICs and to estimate the power variation trend of alpha-band (8-12 Hz) and theta-band (4-7 Hz) to calculate the physiological state index for sending out the corresponded commands to environment controller.

2.3 Environment controller unit

The detailed architecture of the environment controller (EC) is shown in Fig. 5. The EC is composed of a network controller, command decoder and three control endpoints (CEP). Only three specific physiological states, i.e., alertness, slight drowsiness and extreme drowsiness, will be transferred from OMAP1510 to the EC with a TCP/IP envelope. For the network controller in the EC, one can simply design a low-level TCP/IP header decoder to accomplish this controller. Once a/the physiological state is detected by network controller, the command decoder can drive different control endpoints to send out corresponding electrical signals to the demo room. The control algorithm for each control endpoint is denoted as: (1) when alertness: CEP0 (major lamp) ON, CEP1 (night lamp) OFF, CEP2 (fan speed) Full; (2) when slight drowsiness: CEP0 Half ON, CEP1 OFF, CEP2 Medium; (3) when extreme drowsiness: CEP0 OFF, CEP1 ON, CEP2 Slow.

For a practical application, the control endpoint may be far away from the command decoder. To overcome this problem, a remote command decoder and control end point (RCEP) such as wireless or wired Ethernet is practicable and workable.

![Diagram of environment controller](image_url)

Figure 5. Detailed architecture of environment controller, which includes network controller, command decoder and three control endpoints.

2.4 Monitoring host system platform

The monitoring host system has two functions, which include: (1) data storage and real-time status watchdog, such as physiological states and EEG signals display, and (2) DSP processing implementation and uClinux OS development platform. The data size of continuous EEG recordings is beyond the storage capacity of the embedded system. Thus, we have implemented a network file system to store EEG signals. In addition, we built a graphic user interface (GUI) to show the biomedical signals for monitoring. The connection between the host system and the embedded signal processing system is the TCP/IP protocol.

3. Real-time physiological estimator and environment controller

With combining the abilities of online EEG acquisition and wireless transmission, the proposed BCI system is therefore able to analyze the real-time physiological signals. Thus, the real-time physiological state detection approach combined with the environment controller has been implemented for demonstration.

3.1 Experimental environment and EEG data source

A lane-keeping driving experiment [33] triggered by virtual reality (VR)-based cruising environment was designed for cognitive state detection in previous studies [34,35], which successfully evidenced that reaction time (RT) could reflect the driver’s cognitive state directly, e.g., if the subject is alert, the RT should be short, otherwise it is long. In addition, research [23,27,36,37] has also shown that when a subject is going into slight drowsiness (e.g., feels sleepy), the power spectra of alpha and theta bands are both increasing; when the subject is in extreme drowsiness (e.g., deep sleepiness), the power spectra of the theta band keeps on increasing, but the alpha band starts to decrease; when the subject is alert, the power spectra of alpha and theta bands do not have significant variation. This therefore motivates us to employ the EEG signal in [18] and extract the frontal EEG data to be performed with proposed
physiological state detection algorithm to investigate the correlated coefficients between the EEG power spectra of alpha and theta bands and reaction time, and then define the state machine of the environment controller.

3.2 Data processing flow and analyzing design

ICA has been proven an effective technique to remove various types of inevitable EEG artifacts, such as eye movements and blinks, muscle, heart, and line noise, etc., which helps to isolate useful features in relation to the drowsiness levels. However, most of the ICA process is performed offline on a personal computer instead of an online platform. This motivates us to employ on-line ICA decomposition with embedded signal processing unit for cognitive-state index calculation [23,38,39]. The signal analysis procedures are implemented on an OMAP-1510 ARM-based DSP processor, which is provided by Texas Instruments, Inc. The main tasks of the embedded processor are processing EEG data, wireless receiver control, down-sampling, ICA decomposition, the Hanning windowing, short-time FFT and TCP/IP control, etc. Thus, we distributed these tasks into the dual-core processor to retain the required performance.

The acquired EEG signals are down-sampled to 64 Hz to reduce the calculation loading of the system. We use ICA [23,31,32] to decompose the independent components for data analysis. A 64-point Hanning window is applied to smooth the signals before the STFT is processed to extract the time-frequency characteristics of the EEG signals, and a 90-sec window with moving step of 2 seconds is finally applied to eliminate the noise and estimate the processed EEG power spectrum variation of alpha (8-12 Hz) and theta (4-7 Hz) bands for the physiological state-level derivation.

4. Results

A demonstration system of the proposed BCI system is constructed in Fig. 6, which includes: (a) a monitoring host PC for DSP procedure implementation and uCLinux OS development, data storage and real-time status display/watchdog, (b) the environment controller, and (c) a demo room with two fans to evaluate as the air conditioner, two LEDs to evaluate as the day lights, and one LED to evaluate as the night lamp in the real world.

Figure 6. Practical BCI system demonstration which consists of (a) monitoring host PC for data storage and real-time status display/watchdog; (b) environment controller; and (c) a demo room with two fans (c1) to evaluate as the air conditioner, two LEDs (c2) to evaluate as the day lights, and one LED (c3) to evaluate as the night lamp in the real world.

To verify that the proposed BCI system, we firstly tested the modules of biomedical signal amplification/acquisition and wireless transmission in this system with the basic functions. Secondly, the embedded multi-task scheduling mechanism was then tested and compared with the system without scheduling. Finally, to evaluate the performance of the proposed cognitive-state estimation method, the driving performances of six subjects participated in the VR-based highway-driving experiments in different days were compared.

4.1 Basic function test

Because this system is implemented module-by-module, any basic test will make the system more flexible, even for different applications. In our previous research [20], the analog acquisition module and CPLD controller were well verified, so in this investigation, only two basic function tests were applied to verify the wireless receiving path and the ICA processing path. Firstly, we used Matlab to generate a test pattern—a mixture of sine wave with kinds of frequencies less than 30 Hz – and then transmitted this test pattern via Bluetooth on PC. After receiving the test pattern, we dumped the received data and replayed it on a PC. The difference in waveform between the test pattern on PC and received pattern on DSP was almost zero, which indicated the Bluetooth transmission path was correct. Secondary, we generated a mixture signal with four independent signals to observe the correlations of the decomposed ICs off-line operated with PC and on-line operated with the embedded DSP processor to verify the ICA processing path. Table 1 lists correlations of these four components that are decomposed by PC and DSP. Correlations between PC and DSP are 0.9998, 0.9998, 0.8761, and 0.9995 with an averaged correlation of 0.97, which showed the high accuracy of on-line ICA algorithm performed by embedded DSP processor was almost the same as that of the off-line ICA performed by PC. After completing these two path tests, the whole system was then online tested and verified.

| Table 1. Correlations of estimated ICA by PC and DSP platform. |
|------------------|-------------|-------------|
|                  | PC          | DSP         |
| COMP1            | COMP1       | 0.9998      |
| COMP2            | COMP2       | 0.9998      |
| COMP3            | COMP3       | 0.8761      |
| COMP4            | COMP4       | 0.9995      |

4.2 Embedded multi-task scheduling

To ensure an accurate sampling rate for EEG signal acquisition and that data analysis could run in real time, we developed the multi-task scheduling mechanism. Two-channel EEG data with sampling rate of 65 Hz were fed into the proposed BCI system to test the performance of the embedded multi-task scheduling mechanism. The overall execution time results of the proposed BCI system for running a 1000-cycle DSP process with and without embedded multi-task scheduling are shown in Table 2. It took 2589 seconds to complete a 1000-cycle DSP process without multi-task scheduling, while 2008 seconds was used if multi-task scheduling was applied. If
we exclude the time for receiving data, DSP would take 751 and 170 seconds for executing a 1000-cycle data processing with and without multi-task scheduling, respectively. On average, it took 2.008 seconds and 2.589 seconds to complete one data processing cycle with and without multi-task scheduling, respectively. If the time cost of data reception is not considered, the execution time would be reduced from 0.75 seconds to 0.17 seconds with embedded multi-task scheduling. As a result, the embedded multi-task scheduling system was effective to reduce the execution time and ensure the correctness of the received data. It took about 2 seconds to estimate the physiological state, and once the running cycles increased, the performance improved by multi-task scheduling mechanism will introduce an average execution time, which is less than 2 seconds.

Table 2. DSP performance comparison with and without multi-task scheduling mechanism.

<table>
<thead>
<tr>
<th>Execution time (second)</th>
<th>Data receiving time inclusive</th>
<th>Data receiving time exclusive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without multi-task scheduling</td>
<td>With multi-task scheduling</td>
</tr>
<tr>
<td>1000 cycles</td>
<td>2589</td>
<td>2008</td>
</tr>
<tr>
<td></td>
<td>751</td>
<td>170</td>
</tr>
<tr>
<td>One cycle</td>
<td>2.589</td>
<td>2.008</td>
</tr>
<tr>
<td></td>
<td>0.751</td>
<td>0.17</td>
</tr>
</tbody>
</table>

4.3 Physiological state detection

We averaged a 90-sec power spectra gradient of alpha and theta bands and updated it with a 2-second stepping size as the drowsy factors, which are denoted as \( df_{alpha} \), the average power gradient of alpha band, and \( df_{theta} \), the average power gradient of theta band, respectively. The power spectra gradient \( df \) at \( n \)-th update is denoted as \( df(n) \), and the formula is defined in eq.(1):

\[
df(n) = \sum_{k=1}^{T_w} \frac{f_s}{T_s} \ S_k \Delta w
\]

where \( n = 0, 1, 2, 3, \ldots \), and \( T_w \) is the averaged window, \( f_s \) is the sampling rate and \( \Delta w \) is the stepping size. \( S_k \) is the unit power difference, which is defined in eq. (2):

\[
S_k = \begin{cases} 
1, & \text{if } P(k) - P(k-1) \geq \alpha \\
0, & \text{if } |P(k) - P(k-1)| < \alpha \\
-1, & \text{if } P(k) - P(k-1) \leq -\alpha 
\end{cases}
\]

where \( P(k) \) is the power spectra at sample \( k \), and \( \alpha \) is a defined threshold \((\alpha \geq 0)\). The values used in this study were: \( T_w = 9 \) secs, \( f_s = 64 \text{ Hz} \), \( \Delta w = 2 \) secs and \( \alpha = 0.2 \text{ dB} \).

Six subjects’ frontal EEG signals in [18] were investigated to verify the proposed physiological state detection algorithm. The first EEG data collected in the first section was used as the training data to construct a physiological state detection model. The later EEG data acquired in the second section was tested with the physiological state detection model that was derived from first section, to evaluate the physiological state. The correlation coefficients between power spectra in alpha and theta bands and reaction time are listed in Table 3. The averaged correlations for training section and testing section were as high as 98.37% and 78.24%, respectively. We therefore defined three physiological state-level decision rules for the environment controller as follows:

- **S0: Alertness**
  - when \(-0.1 \leq df_{alpha} \leq 0.1 \) and \(-0.1 \leq df_{theta} \leq 0.1 \)
- **S1: Slight drowsiness**
  - when \( df_{alpha} > 0.1 \) and \( df_{theta} > 0.1 \)
- **S2: Extreme drowsiness**
  - when \( df_{alpha} < 0.1 \) and \( df_{theta} < 0.1 \)

Table 3. Comparisons of the estimation performance.

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>98.49%</td>
<td>99.05%</td>
<td>97.92%</td>
<td>97.60%</td>
<td>98.21%</td>
<td>98.95%</td>
<td>98.37%</td>
</tr>
<tr>
<td>Testing</td>
<td>78.14%</td>
<td>81.66%</td>
<td>74.64%</td>
<td>82.65%</td>
<td>75.96%</td>
<td>76.41%</td>
<td>78.24%</td>
</tr>
</tbody>
</table>

4.4 Environment controller

When a different physiological state is detected, the corresponding package will be delivered with the TCP/IP envelope to the environment controller. Then, the command decoder will send out the control commands to the endpoints to drive and control the equipment in the demo room. The related control commands for these three control endpoints are well defined as the following: (1) when the TCP/IP envelope received is S0 (alertness): CEP0 (major lamp) ON, CEP1 (night lamp) OFF, CEP2 (fan speed) Full; (2) when the TCP/IP envelope received is S1 (slight drowsiness): CEP0 Half ON, CEP1 OFF, CEP2 Medium; (3) when the TCP/IP envelope received is S2 (extreme drowsiness): CEP0 OFF, CEP1 ON, CEP2 Slow.

Most often in the real-world application, the control endpoint may far away from the command decoder. To overcome this problem, a remote command decoder and control end point (RCEP), such as wireless or wired Ethernet, are practicable and workable. In our experiment, the wired connection between command decoder and control endpoints are implemented.

5. Discussion and conclusions

A real-time, wireless embedded EEG-based BCI smart living environmental control system with bio-signal processing ability was proposed and successfully demonstrated in this study. It consists of a four-channel physiological acquisition and amplification unit, a wireless transmission unit, a dual-core signal-processing unit, a real-signal display and monitoring watchdog host system, and an environment controller unit. The EEG signal was first acquired by signal-acquisition and amplification unit, and then data was transmitted from the wireless transmitter to the wireless receiver. The received EEG data were processed by the embedded signal processing unit using on-line ICA decomposition, which was mostly operated off-line on a PC, and the processed results were further transmitted to the host system for data storage and real-time display, and also sent out to the environment controller to control the equipment in the...
room by TCP/IP protocol. A multi-task scheduling procedure was employed in the ARM-based dual-core DSP processor for signal-processing to enhance the performance of the embedded system to ensure that this BCI system could work in real-time.

A real-time physiological detection method was also implemented in the developed system for demonstration. Six subjects were on-line tested with the lane-keeping experiment using a VR-based highway simulation environment. The correlations of evaluated and recorded driving performance for these subjects achieve averaged correlations of 98.37% and 78.24% for the training section and testing section, respectively. This study provides the following important technologies: (1) a sensing module for signal acquisition, amplification, and wireless transmission; (2) an embedded system for real-time EEG signal processing; (3) an EEG-based smart living environmental control; and (4) the BCI system that loops a real-time feedback between human and environment equipments.

Moreover, different from other environment control systems, our proposed EEG-based smart living environmental auto-adjustment is suitable for any living human regardless of whether they are motionless or voice/vision impaired. Our motivations to propose this BCI system are: (1) to help people sleep well to enhance their immunity to prevent diseases caused by sleeplessness [4-6,40]; and (2) to give the “ability” to the equipment surrounding those patients with serious motor impairments or vulnerable older people, “knowing” what they should do for these people instead of always being controlled by user.

In conclusion, a flexible BCI platform has been developed and can be applied to various applications in daily life. One of the possible applications is to combine with EMG and a warning stimulus for the patient with sleep-disordered breathing symptom, to prevent them from stopping breathing during extreme drowsiness.

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References


