# Development of Wireless Brain Computer Interface With Embedded Multitask Scheduling and its Application on Real-Time Driver's Drowsiness Detection and Warning

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***Abstract*—Biomedical signal monitoring systems have been rapidly advanced with electronic and information technologies in recent years. However, most of the existing physiological signal monitoring systems can only record the signals without the capability of automatic analysis. In this paper, we proposed a novel brain–computer interface (BCI) system that can acquire and analyze electroencephalogram (EEG) signals in real-time to monitor human physiological as well as cognitive states, and, in turn, provide warning signals to the users when needed. The BCI system consists of a four-channel biosignal acquisition/amplification module, a wireless transmission module, a dual-core signal processing unit, and a host system for display and storage. The embedded dual-core processing system with multitask scheduling capability was proposed to acquire and process the input EEG signals in real time. In addition, the wireless transmission module, which eliminates the inconvenience of wiring, can be switched between radio frequency (RF) and Bluetooth according to the transmission distance. Finally, the real-time EEG-based drowsiness monitoring and warning algorithms were implemented and integrated into the system to close the loop of the BCI system. The practical online testing demonstrates the feasibility of using the proposed system with the ability of real-time processing, automatic analysis, and online warning feedback in real-world operation and living environments.**

***Index Terms*—Brain–computer interface (BCI), electroencephalogram (EEG), online, drowsiness detection, wireless.**

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## I. Introduction

THE ADVANCE in sensor technology and information technology reduces the power consumption of the sensors and make the cost of production cheaper. These trends make it possible to embed sensors in different places or objects to measure a wide variety of physiological signals. A physiological signal monitoring system will be extremely useful in many areas if they are portable and capable of wirelessly monitoring target physiological signals and analyzing them in real time. However, most of the existing physiological signal monitoring systems can only record the signals without the capability of automatic analysis. Recently, with the development of embedded system and signal processing technique, there is a tendency to apply the embedded system technique to brain–computer interface (BCI). An electroencephalogram (EEG) based BCI provide a feasible and noninvasive way for the communication between the human brain and the computer [1]–[7]. Traditionally, the variations of brain waveforms are measured and analyzed by personal computers (PCs). Due to the inconvenience of PC-based BCI that limits the user's mobility, portable and inexpensive BCI platform—small devices with long battery life that can be carried indoors or outdoors—are desired [8].

There are some studies regarding the portable BCI devices [9]–[11]. Gao *et al.* [9] used steady-state visual evoked potential (SSVEP) to control environmental device, such as TV, video tape recorders, or air-conditioners. A portable pocket PC-based BCI was developed by Edlinger *et al.* [10]. In [11], Whitchurch *et al.* developed a wireless system for long term EEG monitoring of absence epilepsy. In [12], Obeid *et al.* proposed a telemetry system for single unit recording. However, these systems mainly focused on the monitoring hardware, but not on real-time analysis. Real-time embedded systems combined with wireless transmission have become a trend of developing diagnosis or homecare systems [13]–[17], because they provide a platform to build sensing and inexpensive BCI systems. Many extended applications may be more practicable to implement on the newer platforms whenever the smaller and more powerful devices are developed.

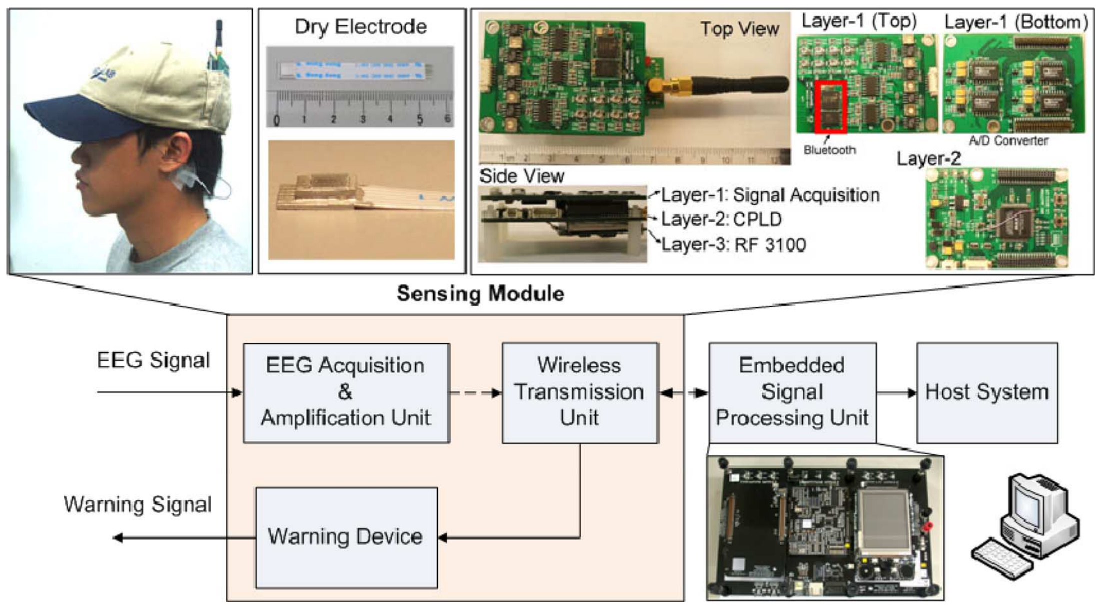


Fig. 1. Block diagram of the proposed BCI system.

The goal of this paper is to develop a real-time wireless embedded EEG-based BCI system that includes four-channel physiological signal acquisition, wireless transmission, and a dual-core embedded system with multitask scheduling. The proposed system employs signal acquisition and amplification units to collect EEG signals, and the wireless module for the transmission of the recorded data can overcome the problem of wiring. With the wireless modules, the subject can carry a light-sensing module instead of wiring to the analysis system that provides the advantage of mobility. The function of the wireless transmission module is selectable between Bluetooth and a custom-made transmission radio frequency (RF) mode depending on different applications and locations. Since the processing of the EEG data needs a large number of calculations, the computing power of the embedded system becomes critical when selecting a suitable embedded processor. Therefore, a dual-core processor integrating a DSP and an advanced reduced instruction set computer (RISC) machine (ARM) processor was used in our embedded system. A multitask scheduling mechanism was also implemented in the embedded system to enhance the real-time signal processing performance. The proposed structure makes it unique to other system designs in terms of its wireless transmission subsystem and dual-core embedded processors for convenient use and powerful computational capability. Finally, a real-time drowsiness detection method combined with an online warning feedback is implemented in the developed BCI system for demonstration. Many traffic accidents on highways are caused by drivers' drowsiness. Our previous studies discovered that some features in human EEG signals are highly related to drowsiness level [18], [19], and they can be used for estimating driver drowsiness. After the online analysis of the EEG data by the multitask scheduling embedded system, the warning device will be triggered when the drowsiness condition occurs.

This paper is organized as follows. The system architecture of the BCI system is introduced in Section II. The system application in real-time driver's drowsiness detection and warning is given in Section III. The results and discussions of the designed system and the application are given in Section IV. The conclusions are summarized in Section V.

## II. System Architecture

The block diagram of the developed EEG-based BCI system is shown in Fig. 1, which includes five units: 1) signal acquisition and amplification unit; 2) wireless data transmission unit; 3) embedded signal processing unit; 4) host system for data storage and real-time display; and 5) warning device. The three-layer sensing module provides 4-ch biomedical signal acquisition, amplification, and wireless transmission functions. The signal acquisition and amplification unit is placed on the top-side of layer 1, and the 8-b A/D converters are designed on the bottom-side of layer 1. Layer 2 is the complex programmable logic device (CPLD) module that controls A/D and wireless modules. For wireless transmission, RF3100 module is arranged in layer 3, and the Bluetooth module is placed on the top-side of layer 1. The size of the sensing module is 4.5 cm $\times$ 6.5 cm $\times$ 2.5 cm, and the weight of the module with a Li-ion battery is 51 g. The sensing module (including signal acquisition, amplification, and wireless units) is 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 continuously operate for at least 45 h with a commercial 16 000 mAh Li-ion battery. In addition, the EEG signal processing unit (OMAP 1510) and the host system (PC) are powered with ac.

### A. *Signal Acquisition and Amplification Unit*

In this paper, the dry electrodes [22] based on microelectromechanical systems (MEMS) technologies were placed on the subject's forehead to acquire the EEG signal because they can overcome the uncomfortableness and inconvenience (e.g.,

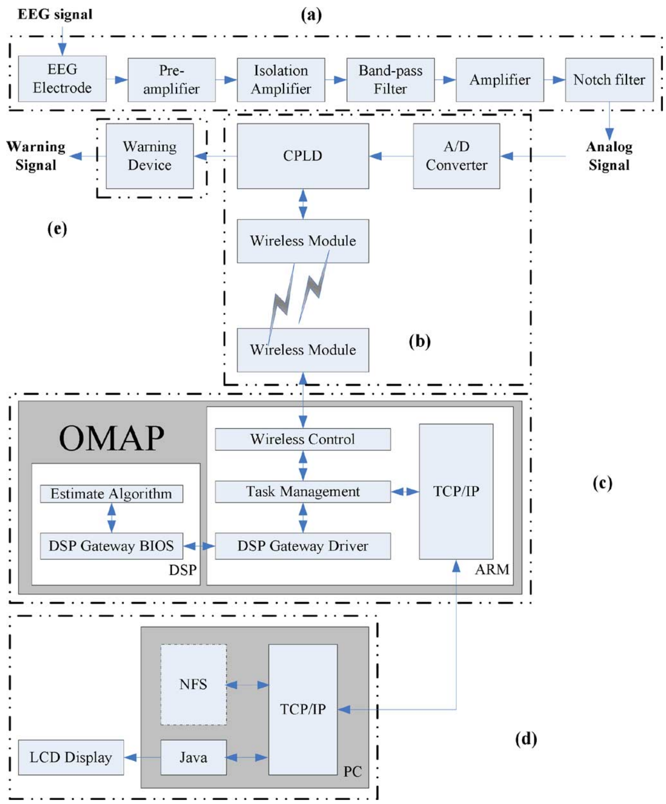


Fig. 2. Detail architecture of the BCI system. (a) EEG acquisition and amplifying unit. (b) Wireless transmission. (c) Dual-core signal processing unit. (d) Remote system for data storage and real-time display. (e) Warning device.

using electrolytic gel) of traditional EEG sensors. After signal acquisition, the amplification unit is applied to filter out the artifacts, as shown in Fig. 2(a). The EEG amplifying circuit consists of a preamplifier (a differential amplifier) with the gain of 100, an isolated amplifier to protect subject, a bandpass filter that was composed of a low-pass filter and a high-pass filter to reserve 1–100 Hz signals, a differential amplifier that had the gain of 10 or 50 (that can be chosen by a switch). The gain of the preamplifier (100) is larger than the amplifier (a gain of 10) because of the EEG signal is in microvolt level, and thus, larger amplification is needed before filtering. The capacity we used in the bandpass filter can compensate the dc-offset, thus there are no mechanism designed for the problem. The sensing module that carried by the subjects is designed to operate with a 3.7-V dc power supply, and the dc voltage can be either supplied by a battery or ac power line. Therefore, a 60-Hz notch filter is also included to eliminate the effect of the line noise in case we have to run the system with ac power.

### B. Wireless Data Transmission Unit

Fig. 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, and wireless modules. The acquired signal is first converted from analog to digital, and then, transmitted through the wireless modules. The ALTERA FLEX10K EPM 7128STC100-7 CPLD is employed

TABLE I
COMPARISON OF THE BLUETOOTH AND RF3100/3105

| Mode | Bluetooth | RF 3100/3105 |
|---|---|---|
| Frequency band | 2.4GHz | 915MHz |
| Transmission distance | 10m | 200-600m |
| Transmission direction | Full-Duplex | Half-Duplex |
| Modulation method | Frequency Shift Keying | Frequency Shift Keying |
| Transmission Power | 0dBm (1mW) | 12dBm |
| Interface | UART、USB | UART |

to control the A/D converter and encode the data for the wireless modules. Two different transmission methods can be selected in the wireless module of the designed BCI system according to the transmission distance in applications. Although Bluetooth module is most commonly used in medical/clinical settings where short-distance transmission is required, long-distance transmission is sometimes desirable in the settings. In addition to drivers' drowsiness estimation, the system is expected to be applied in various fields such as home cares, clinical physiological signal monitoring, and exercise training. Thus, we also integrated a custom-made RF transmission module with longer operation range in the developed system. RF 3100/3105 (Ancher Technology, Inc.) module is a transparent module that integrates low transmission power and high transmission rate (76800 b/s) designs. The comparison of Bluetooth and RF3100/3105 is shown in Table I. 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-ch signal transmission. This setting is quite enough for general EEG signal acquisition since the most concerned frequency band of EEG signals is during 1–60 Hz. The EEG signals are recorded at the higher sampling rate to preserve the original signal as well as possible for various applications in addition to drowsiness estimation. Thus, the signals are recorded at a higher sampling rate and down-sampled to 64 Hz in the EEG signal analysis unit.

### C. Dual-Core Processing Unit

It is expected that the portable biomedical devices should provide more advanced functions such as real-time feedback to the users in addition to online monitoring. Therefore, more complex processing methods have been proposed for physiological analysis, and they will produce more impacts if can be implemented in a real device or product. A dual-core processing unit is adopted as a platform that EEG signal processing methods as well as the intelligent technology can be implemented on it for different applications due to its powerful computation power. The operating core is Texas Instruments (TI) open multimedia architecture platform (OMAP) 1510, which is composed of an ARM925 processor and a TMS320C55x DSP processor. The DSP core was used to process EEG data, and the ARM925 was used to communicate with other devices such as wireless transmission modules and transmission control protocol/ internet protocol (TCP/IP) network. The DSP gateway is used as the

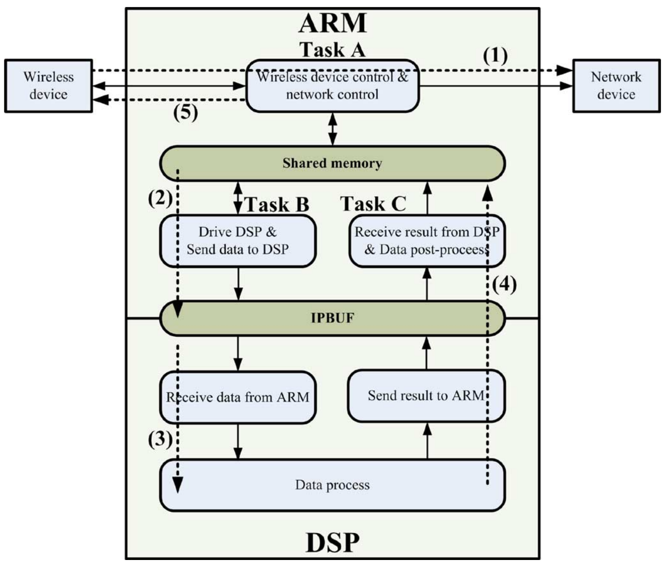


Fig. 3. Software structure of the embedded system and the data processing flow.

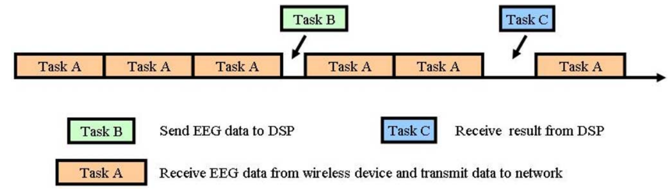


Fig. 4. Time series diagram of multitask scheduling mechanism.

cooperation structure for the communication between the two cores since these two cores have different functions, as shown in Fig. 2(c). The DSP gateway is software that makes ARM core possible to use resource of DSP core by application program interface (API), and works like a small real-time kernel that manages the resource and data flow in the DSP core. With this mechanism, the DSP processor is on only when the system needs to process the EEG data. The Linux operating system (OS) is built to manage the resource of ARM core [20]. The functions of ARM core can be divided into three parts: 1) wireless module control; 2) TCP/IP control; and 3) DSP gateway driver. The ARM core was selected for these tasks due to its excellent interface control ability. The process flow and task distribution in the embedded system are shown in Fig. 3.

There are two processing flows running at the same time including EEG data acquisition and communication and EEG signal processing. The data processing flows are described as follows. 1) After receiving EEG data from wireless device, task A transmits the data to network. The EEG data are then stored in the shared memory. 2) After the EEG data are stored, task B enables the DSP module and sends data to DSP. 3) After DSP receives the EEG data, DSP processes the data with Hanning Window and short time FFT analysis. 4) After EEG analysis, DSP sends the result to ARM and ARM performs the other processes and saves the result to the share memory. 5) If the driver drowsiness is detected through EEG analysis, the embedded system will send the triggering signal to the warning device via wireless transmission.

Since the proposed BCI system is designed to work in real-time, the signal-receiving task should continue while EEG signal is on processing. An embedded multitask scheduling mechanism system is used to manage these tasks and to ensure the accurate sampling rate for EEG signal acquisition and data process/analysis in real time [21]. The tasks are divided into three types according to their working frequency: 1) task A—wireless device and TCP/IP control; 2) task B—call DSP task and transmit EEG data to IPBUF buffer; and 3) task C—receiving data from IPBUF buffer and further processing of the DSP processed data. The time series diagram of the multitask scheduling system is shown in Fig. 4. The working frequency of buffer IPBUF data transmission is much smaller than the working frequency of wireless device and TCP/IP control. Thus, we allowed the system continuously to receive signals from the wireless module and output to the display unit through TCP/IP. The system can decide when to process other tasks by itself. With the architecture, the ARM core will not only hold and wait, but also keep transmitting data from the wireless module to the display unit when the DSP core is processing the EEG signals. Interprocess communication (IPC) is also an important issue for our scheduling system since the tasks in our system are not completely independent. In our system, ARM-Linux was used to manage tasks. Linux provides three methods for IPC: message queue, semaphore, and shared memory. Message queue and semaphore are not efficient enough for the proposed embedded system. Three modified communication methods are employed in the proposed BCI system for IPC: 1) a novel synchronization mechanism; 2) arbitration method; and 3) sharing memory buffer (IPBUF) between processing cores. Traditionally, the synchronization procedure is enabled when two tasks are accessing one memory block at the same time. The memory is blocked when one task is writing or reading on it, thus no other task can access to the memory. The synchronization procedure unlocks the blocked memory when the first task finishes writing/reading, and then, sends a signal to inform other waiting tasks. It is obvious that the mechanism can largely decline the processing speed of the processor. A new synchronization mechanism is designed to deal with the simultaneous memory access by both receiving EEG data from EEG acquisition system (task A) and sending EEG data to DSP (task B). When task A is accessing the memory, task B will be idle and waste some time in waiting. Therefore, we use two blocks of memory with the same size to reduce the waiting time. When task A is storing EEG data on memory M1, task B can get the EEG data from memory M2 at the same time. With the modified procedure, these two tasks can execute concurrently and reduce the waiting time caused by synchronization control. Although the method consumes double memory size to complete the procedure, the required extra memory is less than 4K B. Besides, we use arbitration flag register instead of semaphore due to that the speed of flag register based on shared memory is the fastest IPC method in Linux platform. In addition, using flag register can reduce the amount of memory needed because one declared variable can contain many flags.

### D. Host System for Data Storage and Real-Time Display

The structure of the host system is shown in Fig. 2(d). The host system has two functions including data storage and real-time EEG signal display. 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. Additionally, we built a graphic user interface (GUI) to show the biomedical signals in real time, as shown in Fig. 6(c). The connection between the host system and the embedded system is TCP/IP protocol.

### E. Warning Device

The warning device is combined in our system, as shown in Fig. 2(e). Visual signal and audio signal can be presented to the BCI users as the feedback warning signals. The audio signals are more effective in our prior study for driver drowsiness warning since it is easier to detect audio signals than visual signals for the driver when he/she is drowsy. The efficiency of audio signals with different frequencies, 500, 1750, and 3000 Hz, were tested in the prior study and the audio signal of 1750 Hz achieves the best results. The triggering signals are sending from the dual-core EEG signal-processing unit to the warning device through wireless transmission modules. The RF3100/3105 modules are half-duplex, which means that the modules cannot transfer and receive signals at the same time. Since the signals are transmitted as packages, a package of warning signal can be transmitted in the time period between two packages of the acquired EEG signals for transmission. The time period between two packages might be too short for the reverse-direction transmission if the transmission frequency is set too high. To deal with the problem, the transmission frequency is set lower to leave some time duration for the data transmission from the other end.

## III. Real-Time Driver's Drowsiness Detection and Warning

With combining online EEG recording and wireless transmission ability, the proposed BCI system is designed for real-time physiological signal analysis. Thus, a real-time drowsiness detection method combined with an online warning feedback is implemented in the developed BCI system for demonstration. A dynamic operating environment is also built up to test and verify the robustness of the BCI system.

### A. Experiment Environment and Experimental Design

A virtual reality (VR) based highway-driving environment reported in our previous studies [18], [19] was used to investigate those changes on drivers' cognitive states in long-hour driving tasks. The VR driving environment includes 3-D surround scenes projected by seven projectors and a real car mounted on a 6-degree-of-freedom Stewart platform to provide the kinesthetic stimuli. The driving speed is fixed at 100 km/h, and the car is randomly and automatically drifted away from the center of the cruising lane to mimic the consequences of a nonideal road surface. The subject was asked to keep the car on the third lane (from left to right). Driving error is defined as the deviation between the middle of the car and the middle of the third lane. While the subject is alert, his/her response time will be short, and deviation of the car will be small; otherwise, the subject's response time will be slow and the car's deviation can be large. After 90 sec moving average, the driving error are then normalized to 0–100. The driving error is related to the driver's response time and is considered as the index of the driver's drowsiness level in this paper. Electrode caps are usually used for EEG signal acquisition in most of applications. However, the traditional wet electrode requires electrical gel to increase the conductivity between the electrode and the scalp. Thus, it takes time for preparation, and the subjects need to wash their hair after recording. For the convenience in practical applications, we place four dry electrodes [22] on the driver's forehead and the distance between two near electrodes is 1.5 cm to acquire the EEG signals for the BCI system. The EEG features related to alertness changes can be extracted from EEG signals acquired by the electrodes at the forehead according to our experiments. Therefore, placing electrode array on the forehead is a feasible and convenient strategy for drivers' drowsiness estimation. Six dry electrodes are used to acquire EEG signals from the driver including five electrodes placed on the subject's forehead and one placed behind the subject's left ear. The five electrodes we placed on subject's forehead including a common ground electrode and four EEG electrodes. The ground electrode is directly connected to the ground of power supply. The EEG signals we used in further analysis are measured between the four EEG electrodes and the reference electrode. The dry electrodes and the sensing module can be embedded in a hat, as shown in Fig. 1. The combination of the dry electrodes and the sensing module has gradually improved the convenience and the future applicability of the developed system.

### B. Data Processing Flow and Analyzing System Design

The analysis procedure implemented in the dual-core signal processing unit is shown in Fig. 5. The acquired EEG signals are first down-sampled to 64 Hz to reduce the calculation loading of the system, and a 64-pt Hanning window is then applied to smooth the signals. The short-time Fourier transform is used to extract the time–frequency characteristics of the EEG signals, and a 90-sec moving average filter is applied to eliminate the noise. We use principal component analysis (PCA) on the EEG power spectrum to reduce the data dimension and the computational loading of the embedded system. The EEG features (dimension $= 20$) extracted by PCA are then fed into a linear regression model to estimate the driver's drowsiness levels. The EEG signals collected in the first session were used to construct his/her drowsiness estimation model including the PCA method through offline training by the PC. The model including the PCA matrix is then load into OMAP 1510 to process and analysis the subject's EEG signals in the other days in online and real-time for testing.

The main tasks of the embedded processor OMAP1510 was to process EEG data, wireless receiver control, and TCP/IP control. Thus, we distributed these tasks into DSP core and ARM core to retain satisfied performance. According to the

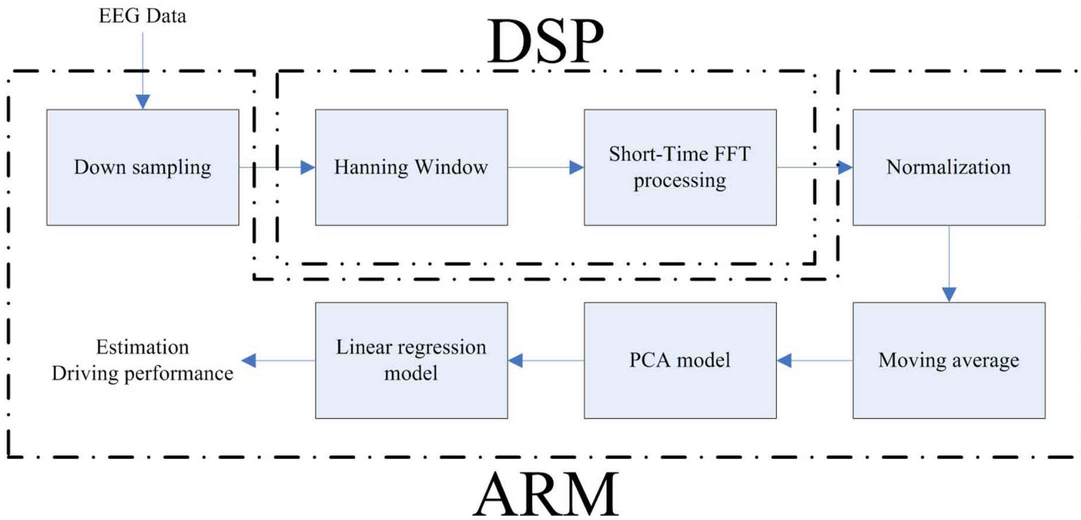


Fig. 5. Flowchart of the proposed EEG signal analysis procedure.


Fig. 6. Testing results of the acquisition/amplifying unit and the developed GUI monitoring interface.

characteristics of the processors, the calculation of driving error estimation needed to process a long period of EEG data, so it was implemented in ARM processor. On the other hand, the Hanning windowing and short-time FFT needs heavy computation, and thus is implemented in the DSP core to balance the computation load. The remaining processes were implemented in ARM because they need relatively less computations.

## IV. Experimental Results

The feasibility of the proposed BCI system is tested in three aspects. First, we test the basic functions including biomedical signal amplification/acquisition and wireless transmission of the system. The embedded multitask scheduling system will then be tested and compared with the system without scheduling. Finally, the accuracy of the embedded drowsiness monitoring system will be evaluated.

### *A. Test of the Basic Functions*

The basic functions of the developed BCI system should be tested before any further applications. The subsystems are designed in modules to make the system more flexible for different applications. Thus, the test of the system can be divided into two phases, the subsystem testing and the overall-system testing. The acquisition/amplifying unit is tested for its dependability by three steps. First, a sin wave with frequency of 5 Hz and 30 $\mu$V vibration amplitude generated by the EEG simulator is used for simulation test. Then, EEG signals of eye blinking were test because the amplitude of the signals will be larger, and it is easy to be recognized from acquired signal. Finally, we want to measure $\alpha$ wave to confirm that the signal we measured is real EEG signal. When subjects take rest and close their eyes, we can continuously measure $\alpha$ wave with frequency band between 8 and 12 Hz. Fig. 6(b) shows the $\alpha$ wave measured by the developed system.

After tested and verified the subsystems, we test and verify the whole system online. In order to show the processed results of our system, we developed a Java GUI to receive the processed results of the embedded system by TCP/IP network and plot them on the display screen, as shown in Fig. 6(c). The left two frames are two-channel EEG raw data (frames A, B), and the right frames show the estimated drowsiness levels (frames C, D).

TABLE II
COMPARISON OF THE PERFORMANCE

| Execution time (second) | Considering the time of data receiving | | Without considering the time of data receiving | |
|---|---|---|---|---|
| | Without multi-task scheduling | With multi-task scheduling | Without multi-task scheduling | With multi-task scheduling |
| 1000 cycles | 2425 | 1933 | 587 | 95 |
| One cycle | 2.425 | 1.933 | 0.587 | 0.095 |

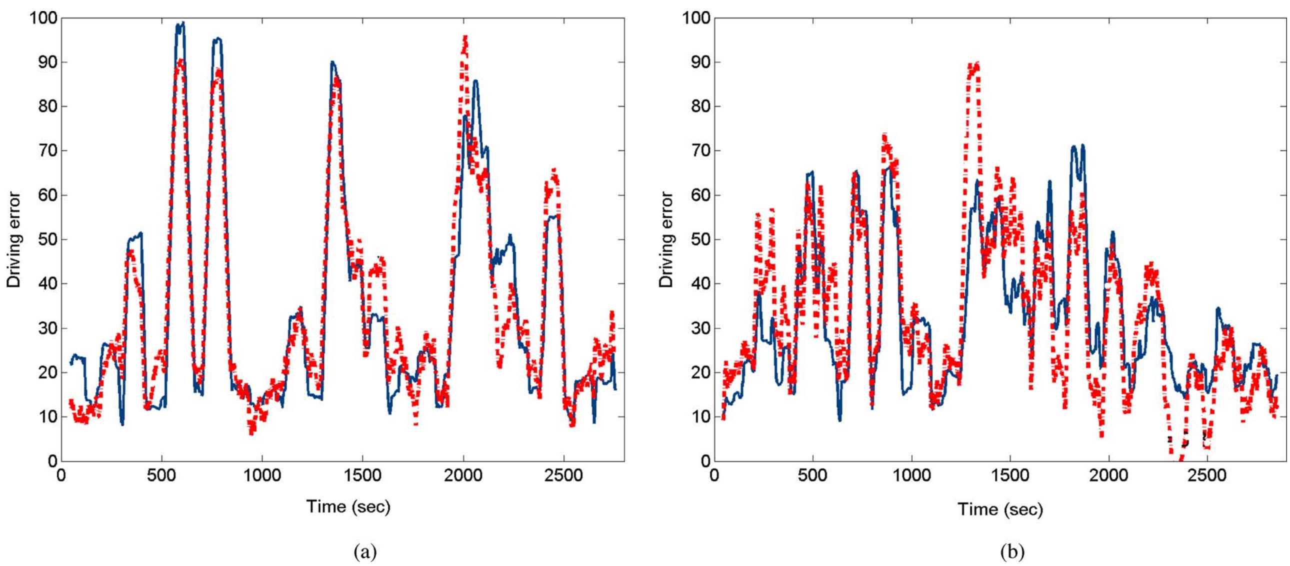


Fig. 7. Drowsiness level estimation implemented on the embedded BCI system for a session based on a linear regression (dashed line) of PCA-reduced EEG log spectra, overplotted against actual driving performance time series for the session (solid line). (a) Training session performance. (b) Testing session performance.

### *B. Embedded Multitask Scheduling*

The multitask scheduling mechanism was developed to ensure the accurate sampling rate for EEG signal acquisition and data analysis in real time. In order to test the performance of the embedded multitask scheduling system, two-channel EEG data with sampling rate of 65 Hz were fed to the BCI system. The time consumptions of BCI system executing 1000 cycles of signal processing procedure in DSP with and without embedded multitask scheduling are compared, and the test results are shown in Table II. It takes 2425 sec to complete the 1000 cycles without multitask scheduling, whereas the system with multitask scheduling needs only 1933 sec. It is noted that the execution time is mainly used in receiving data. It takes 1838 sec for the system to receive data, which means it takes only 95 and 587 sec for 1000-cycle data processing with and without multitask scheduling, respectively. In average, it takes 1.933 and 2.425 sec to complete one data processing cycle (the drowsiness level in 2 sec) with and without multitask scheduling, respectively. If the time cost of data reception is not considered, the executing time will be reduced from 0.6 to 0.1 sec with embedded multitask scheduling. As a result, the embedded multitask scheduling system is useful to reduce the execution time and ensure the correctness of the received data. It takes about 1.933 sec to calculate a value of driving error. The result is shown in frame C of Fig. 6(c) as a peak. The time interval between two peaks is about 2 sec.

TABLE III
COMPARISONS OF THE ESTIMATION PERFORMANCE

| Subject | 1 | 2 | 3 | 4 | 5 | Average |
|---|---|---|---|---|---|---|
| Training | 97% | 96% | 86% | 95% | 93% | 92.6% |
| Testing | 77% | 85% | 58% | 72% | 81% | 74.6% |

### *C. Drowsiness Detection*

In order to test and verify the feasibility of applying the developed embossed BCI system into practical applications, the drowsiness detection method proposed in Section III was implemented in the BCI system for online testing. Two different sessions of EEG signals are acquired in different day for each subject. The EEG data collected in the first session is used as training data to construct a driving error estimating system. The EEG data collected from the second session is then applied to the constructed estimating system to predict the drowsiness levels of the driver. The result is shown in frame C of Fig. 6(c) as a peak. The time interval between two peaks is about 2 sec. The amplitude of the peak represents the estimated driving error calculated by the drowsiness estimating system. The subject is considered drowsy if the value of driving error is bigger than a threshold and the warning device will be triggered. The correlation coefficient between the predicted drowsiness levels and the actual driving error acquired in the second session is calculated as an index of the system performance.

TABLE IV
COMPARISON OF BCI SYSTEMS

| BCI System | Gao [9] | Whitchurch [11] | Obeid [12] | Graz-BCI [10] | The proposed system |
|---|---|---|---|---|---|
| Signal | EEG | EEG | Single unit | EEG ECG/EOG | EEG/EMG ECG/EOG |
| Channels | 2 | 6 | 16 | 8 | 4 |
| Transmission | Wire | Bluetooth | WLAN IEEE802.11b | Wire | Bluetooth/RF |
| Resolution of A/D | 12 | 12 | 8 | 16 | 8 |
| Sampling Rate | 200 | -- | 244 | 256 | 457 |
| Gain | -- | 10000 | 500/1000 | -- | 1000/5000 |
| Filter | 4~35Hz band pass 50 Hz notch | 60 Hz low pass | 211 Hz high-pass | -- | 1~100Hz band pass 60 Hz notch |
| Signal Processing Unit | DSP | notebook | 66MHz AMD processor | PDA | Dual-Core DSP |
| Analysis Procedures implemented in the Portable Device | 1. FFT 2. Feature extraction | -- | -- | FFT | 1. Down sample 2. Hanning window 3. FFT 4. Normalization 5. Moving average 6. PCA 7. Linear regression model |

The training and testing results of the drowsiness level estimation for subject 5 is shown in Fig. 7. The dash line in Fig. 7 indicates the drowsiness level estimated by the BCI system and the solid line is the acquired driving error. The comparison of the estimating performance for five individual subjects is given in Table III. The average correlation between the estimated and the acquired data among the five subjects can reach to 75%.

### D. Comparisons and Discussions

The specifications of the proposed BCI system and the other existing systems are concluded in Table IV. Gao *et al.* [9] proposed an environmental controller using a BCI technique based on SSVEP, and the system consists of a stimulator, a digital signal processor, and a trainable infrared sensing controller. They applied a FFT and a feature extraction mechanism in DSP to control the electric apparatus. The Graz-BCI [10] is a cue-based system using the imagery of motor action as the appropriate mental task. Whitchurch *et al.* [11] devised a wireless monitoring system based on Bluetooth to enable the physician to monitor the EEG when the patient resumes his/her normal activities for the reason that the transmission band (2.4 GHz) is allowed in hospital. Obeid *et al.* [12] developed a 16-channel sensing telemetry system to facilitate multichannel single unit recordings from freely moving test subjects. The 16-channel signals derived from implanted neural electrodes were transmitted through IEEE 802.11 b. It only can work for 45 min without power supply due to large power consumption. Regarding to the proposed system, we used two different wireless transmission modules to ensure the flexibility of the proposed BCI system since the transmission distance of Bluetooth can only cover 10 m, while the RF module can cover more than 200 m. Users can easily switch between the two wireless modules depending on different application environments. Seven procedures were implemented in the signal-processing unit, and the real-time capability is also guaranteed due to the developed embedded multitask scheduling mechanism. It can also provide online warning signals when the abnormal state of uses such as drowsiness in driving appears.

## V. CONCLUSION

A wireless embedded BCI system with real-time biosignals processing ability is proposed in this paper. It consists of a four-channel physiological acquisition and amplification unit, a wireless transmission unit, a dual-core signal-processing unit, a sensing real-signal display and monitoring unit, and a warning device. The EEG signal was first acquired by signal-acquisition and amplification unit, and then, transmitted from wireless data transmitter to wireless data receiver. The wireless-transmitted EEG signals were processed by the data processing unit, and the processed results were further transmitted to the sensing system for data storage, real-time display, or triggering the warning devices by TCP/IP. A multitask scheduling procedure was employed in the dual-core signal-processing unit to enhance the efficiency of the embedded system and make sure the BCI system can properly work in real-time. A real-time drowsiness detection method combined with an online warning feedback was also implemented in the developed system for demonstration. This research provides the following important technologies: 1) a sensing module for signal acquisition, amplification, and wireless transmission; 2) a dual-core embedded system for real-time EEG signal processing; and 3) an automatic bio-feedback loop for online warning and reminding. With combining all the technologies, a flexible BCI platform is developed and can be applied to various applications.

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