Design Concept of a Wearable Device for Sleep Related Brain Wave Detection and Stimulation

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***Abstract*—This paper presents a design concept of an innovative wearable device for brain wave detection and stimulation to aid sleep. Sleep's importance for a healthy life emphasizes the value of studying the application of technology to improve sleep quality for individuals unable to receive a good night's rest. Utilizing electroencephalography (EEG) for accurate sleep tracking, the device aims to be portable and efficient. It includes the EEG sensing and processing module, adaptive control and machine learning module, and electronic stimulation module, working together to guide the brain toward relaxation. Preliminary results demonstrate promising performances or necessities of the subsystems of the proposed design.**

Keywords*—*Adaptive control, EEG, machine learning, sleep, wearable device

I. Introduction

Sleep is a complex process involving active unconsciousness, with the brain in a relatively restful state and responsive to internal stimuli. Sleep allows the body to repair and refresh essential components and is also crucial for neural reorganization and brain development. However, many people are affected by sleep disorders such as insomnia. Insomnia is a condition where disruptions in sleep lead to many issues in the daytime, affecting about 10% of the global population, with a preponderance of females [1]. It can be acute or chronic, with various potential causes including genetics, brain activity differences, medical or mental health conditions, life circumstances, and sleep habits. While usually not dangerous, insomnia can significantly impact quality of life.

Although insomnia is manageable with medications, we aim to develop a more convenient, non-medication-based method to promote the sleep quality of people with sleep problems. In this paper, we present a design concept of a wearable device for brain wave detection and stimulation, which is primarily used for sleep aid. One of the most accurate methods for sleep tracking is using electroencephalography (EEG), which measures brain activities [2]. Since brain activities have different patterns in different sleep stages, we can track sleep by analyzing EEG signals. However, most EEG acquisition devices are bulky and expensive—they are neither convenient nor economical for domestic use. Our goal is to develop a portable, low-cost EEG acquisition and brain stimulation device empowered by advanced adaptive control algorithms. The EEG acquisition module is integrated with a microcontroller system and a transcranial electrical stimulation (tES) module for sleep aid. This device can also be easily extended in the future for managing anxiety, training people to focus their attention, and improving cognitive performance.

The rest of the paper is organized as follows. Section II briefly reviews the related works on wearable devices for sleep monitoring and sleep aid. Section III explains our proposed system design concept and methods, and Section IV presents some preliminary results. Conclusions are given in Section V.

II. Related Works

A. Sleep Physiology

Sleep alternates between two main phases, the non-rapid eye movement (NREM) and rapid eye movement (REM) phases. NREM is further divided into three stages: N1, N2, and N3 stages. Sleep begins with NREM N1-N3 stages and then is continued by REM. REM and NREM cycle throughout the night, as NREM makes up 75-80% and REM 20-25% of total sleep [3]. Sleep is regulated by a balance between homeostatic processes, which is the drive for the need for sleep, and the circadian rhythm, which is an internal clock controlling the sleep-wake cycle. Polysomnography, the primary test for studying sleep, includes EEG, electrocardiogram (ECG), electrooculography (EOG), electromyography (EMG), and oxygen saturation measurements to provide information on a patient's sleep status. These can be used to diagnose specific sleep disorders by looking at brain, cardiac, eye, muscle, and respiratory functions during sleep. In medical practices for sleep stage classification, physicians prefer to use EEG signals rather than other physiological measurements because EEG signals contain rich information about sleep [2].

B. *Wearable Devices for Sleep Monitoring*

Several studies have been conducted for sleep monitoring using wearable devices. One direction of research is to use wearable devices to measure heart rate variability (HRV) in order to identify different stages of sleep. For example, wrist-based HRV watches are used to measure heart rate and analyze the intervals of one's heart rate to predict different sleep stages [4]. Chest bands/electrodes can be placed directly on the body making it easier to provide accurate data [5]. However, the HRV watches have poor results in accurately identifying the sleep stages, while the chest bands and electrodes are difficult in practical use. In addition, there are also mattress or pillow monitors that measure heart rate [6], but being so distant from the body causes an even bigger accuracy issue than with the wristbands. Another direction of research delves into evaluating a specific wearable device for sleep monitoring called an actigraphy device [7]. These devices use actigraphy technology, by employing accelerometers to monitor movement patterns while one is sleeping. This method offers non-intrusive and easy-to-wear features, which allow users to wear it comfortably during sleep. The device also allows users to access their movement patterns, to keep track of their sleep-wake cycle, and the quality of their sleep. However, the device does not address several challenges, such as the accuracy of different sleep stages and external factors.

C. *Commercial Sleep Aid Devices*

Current forms of commercial sleep aid devices include smart sleep masks, alarms, and wearable bracelets. Smart sleep masks on the market come with speakers which produce music to assist sleep and lights to simulate the experience of a sunrise. The company Bia currently sells a smart sleep mask that uses their neurofeedback technology, taking in brain activities through near-infrared spectroscopy and outputting mechanical vibrations through the foam on the mask [8]. Another form of sleep aid, such as the Apollo® Wearable [9] (a wearable bracelet), utilizes physical vibrations to connect to one's nervous system, encouraging relaxation. Other tabletop devices such as alarms aim to aid with sleep through the emission of certain types of light or sounds, such as music or white noise, to encourage sleep. The Restore 2 by Hatch uses soothing sleep sounds and colors to either calm a user before falling asleep or to emit a sunrise-like hue alongside an alarm [10]. These devices lack personalization and are less effective due to indirect stimulation of the brain or unavailable or inaccurate estimation of brain status.

III. METHODS

The overall architecture of the proposed design is summarized in Fig. 1. It consists of three basic modules: a sensor—EEG sensing and processing module, a controller—adaptive control and machine learning module, and an actuator—electronic stimulation module.

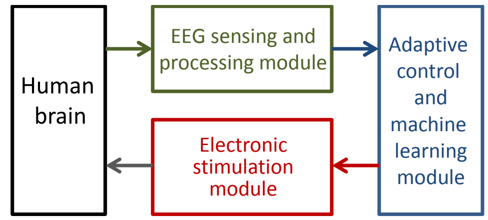


Fig. 1. Overall system architecture.

A. *EEG Sensing and Processing Module*

The functions of the EEG sensing and processing module are to collect, amplify, filter, and digitize the EEG signals and then transmit the processed signals to the controller module. It consists of three signal processing units, in addition to the battery unit and communication unit (which are not discussed here). The first signal processing unit is a high-pass filter with a high-frequency gain of 10, which is implemented by an instrumentation (precision) amplifier coupled with an integrator circuit realized by a general-purpose operational amplifier (op amp) with a resistor in the feedforward path and a capacitor in the feedback path. The second unit is a 4th-order low-pass filter whose DC gain is 600 and whose cutoff frequency is adjusted to be around 30 Hz. A cutoff frequency of 30 Hz is low enough to help block the 60 Hz noise from the electrical power lines, while high enough for the filtered EEG signals to contain sufficient powers of the four major brain waves related to sleep detection: alpha, beta, theta, and delta waves. The low-pass filter unit includes four general-purpose op amps, one serving to produce a pure gain of 100, two—together with resistors and capacitors—realizing the desired low-pass characteristics in the frequency response, and the last op amp producing an additional gain of 6. The third signal processing unit is a driven right leg (DRL) circuit, which helps reduce common-mode interference. We know that the human body can pick up electromagnetic interference, especially the 60 Hz noise from electrical power lines, which may obscure the EEG signals of tiny amplitudes. Besides the low-pass filter, the DRL circuit can further suppress the 60 Hz noise through a high-gain feedback mechanism.

B. *Adaptive Control and Machine Learning Module*

The adaptive control and machine learning module, or the controller module, has two units. The first unit performs machine learning, which mainly aims to estimate the brain status. The second unit handles adaptive control that (i) calculates control signals to drive the actuator module and (ii) adaptively tunes the parameters of the frequency response model of the brain and the other parameters of the controller.

The machine learning unit estimates the brain status by classifying the sleep/wakefulness stages. We have already developed a semi-supervised learning architecture which combines clustering algorithms and supervised learning algorithms to address the challenge of deficiency in labeled sleep data [11], [12]. We have also studied the dimensionality reduction problem in sleep detection using EEG data [13], [14]. To further reduce the computational load of machine learning, we here develop an ensemble learning framework that trains multiple sub-models and integrates the results from the sub-models to produce a single decision or prediction (Fig. 2). Different sub-models are trained using the labeled data from different human subjects. When predicting the overall model's outcome for new data input, the ensemble learning algorithm calculates the confidence level for each sub-model (classifier C_i in Fig. 2, where i ranges from 1 to N) and uses these confidence levels to determine the weights and combine the results from the sub-models to form a final decision. The algorithm gives higher weights to sub-models with higher confidence levels—higher levels imply that these sub-models' training datasets are more similar to the new data input. Therefore, the ensemble learning framework can effectively address the issue of varying EEG data distributions among a population of human subjects.

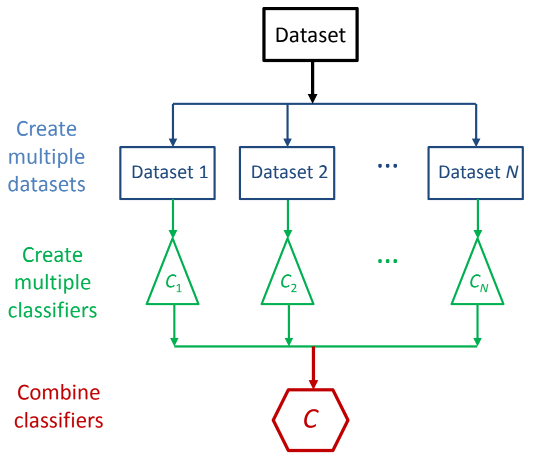


Fig. 2. Ensemble learning framework.

The adaptive control unit of the controller module calculates the control command based on the estimated brain status to drive the actuator module, which in turn delivers the transcranial electrical stimulation (tES) to the brain. The adaptive control unit has a double loop structure: an inner loop and an outer loop. The inner loop relies on a mathematical model to predict the resonant behavior of the brain in response to tES and determines the optimal amplitude, frequency, and waveform of the tES signal. The parameters of the model as well as the inner-loop controller are adaptively tuned by the outer loop controller. The tuning algorithm is designed based on mechanisms of system identification and reinforcement learning. It is known that tES with either direct current (DC) or alternating current (AC) can be used to enhance or disrupt brain oscillations, but it is still unclear how the parameters of stimulation should be individualized to optimize stimulation performance [15]. The adaptive control unit proposed here is expected to solve the tES parameter individualization and optimization problem. Also note that the same controller architecture introduced in this paper can be readily generalized for the other means of brain stimulation such as sounds or mechanical vibrations.

C. Electronic Stimulation Module

The electronic stimulation module, or actuator module, is to implement the command from the controller module, i.e., to generate tES signals of desired strengths, frequencies, and waveforms. The actuator module consists of two major units (besides the battery unit, which is not discussed here): one for providing a current source with adjustable amplitude and the other for generating an AC signal of tunable frequency and waveform. A circuit diagram for the current source unit is shown in Fig. 3(a). Due to the high-gain feedback from an op amp, we can show $I_{\text{load}} \approx I_{\text{sense}} = V_{\text{ref}}/R_{\text{sense}}$, so I_{load}, the current provided for the load (which is adjustable as V_{ref} may be tuned by a microcontroller), can be maintained near the level $V_{\text{ref}}/R_{\text{sense}}$ when the magnitude of the load impedance Z_{load} is no greater than a certain value. A simplified circuit diagram for the AC signal generator is shown in Fig. 3(b), where the current source I_{supply} is produced by the current source unit (Fig. 3(a)) and the gates G_1, G_2, G_3, G_4 are controlled by a microcontroller (not shown in the diagram). The switching patterns of these four gates will determine the frequencies and waveforms of the generated AC signals.

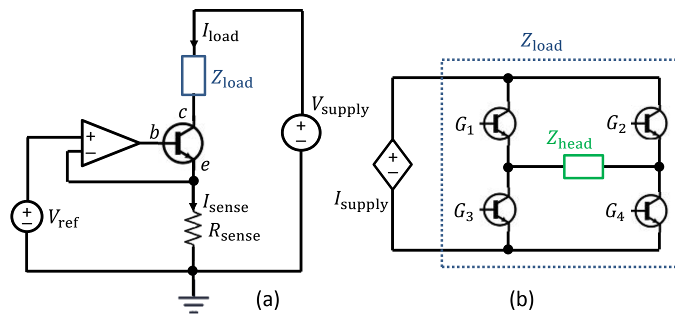


Fig. 3. Electronic stimulation circuit diagrams. (a) Circuit for realizing a current source. (b) Circuit for AC signal generation.

IV. Preliminary Results and Discussions

The whole project is still in progress, but in this section we are able to present some preliminary results from two sub-tasks: (i) EEG signal processing (related to the design of the EEG sensing and processing module) and (ii) justification of the need for ensemble learning (related to the design of the adaptive control and machine learning module).

A. EEG Signal Processing

We developed a circuit board (Fig. 4) to implement the three signal processing units as described in Section III-A. The EEG signals were collected from a graduate student in our lab when he was awake. During the experiment, two EEG electrodes were placed on the forehead and the temple, respectively, and the DRL electrode on the tip of the nose. Fig. 5 shows examples of two filtered EEG signal segments and their frequency contents, one without and the other with eye-blink artifacts. Both the time-domain and frequency-domain plots show satisfactory amplification and de-noising performances of the filters. To further demonstrate the effect of the DRL circuit, we generated a 100 μV, 10 Hz sinusoidal signal using a signal generator and a voltage divider, and then mixed the signal with the 60 Hz noise from the power lines through a human body impedance model. Fig. 6 shows the filtered signals with and without using the DRL circuit, respectively. It is apparent that the 60 Hz noise was significantly suppressed by using the DRL circuit.

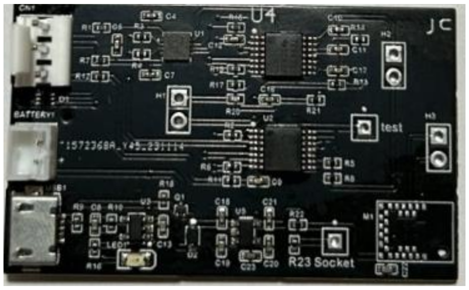


Fig. 4. Developed circuit board (5 cm × 3 cm) for EEG signal processing.

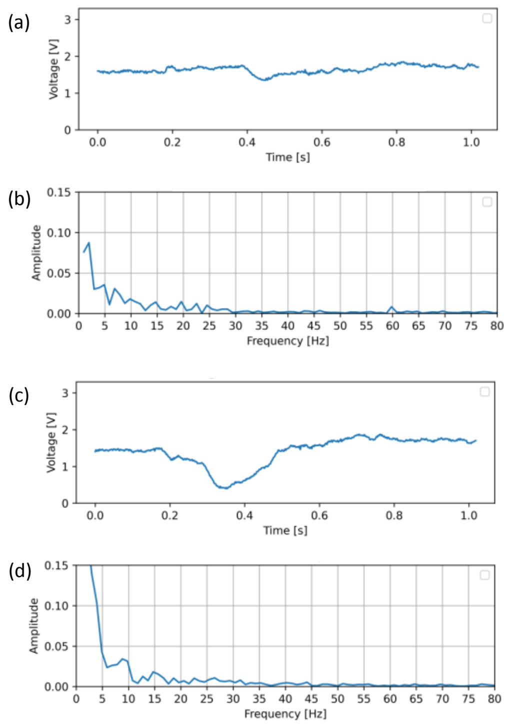
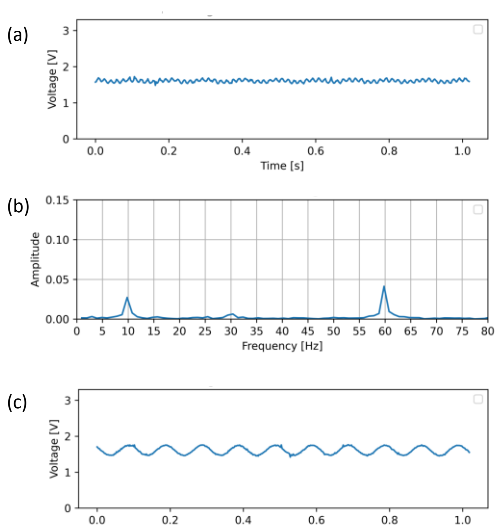


Fig. 5. Examples of processed EEG signals from an awake human subject. (a) and (c): Time-domain signals without and with eye-blink artifacts, respectively. (b) and (d): Frequency-domain plots for the signals in (a) and (c), respectively.



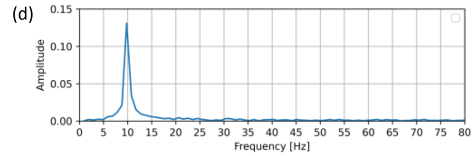


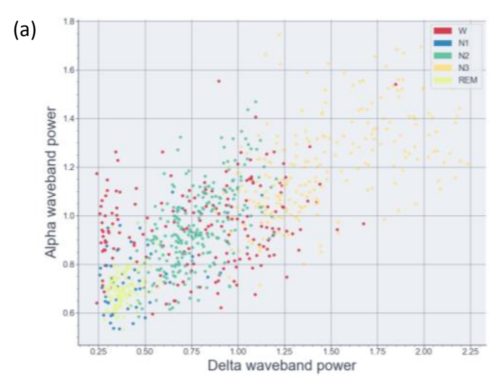
Fig. 6. Effects of driven right leg (DRL) circuit. (a) and (c): A sinusoidal signal of 10 Hz contaminated by the 60 Hz noise was filtered without and with DRL circuit, respectively. (b) and (d): Frequency-domain plots for the signals in (a) and (c), respectively.

B. *Justification of the Need for Ensemble Learning*

To test machine learning algorithms, we used data from a public database called PhysioNet [16], which contains EEG signals from a group of human subjects aged 21-35 years not on any medication.

The EEG signals were processed using band-pass filters to extract signals of four frequency ranges: delta wave (1-4 Hz), theta wave (5-8 Hz), alpha wave (9-12 Hz), and beta wave (13-30 Hz). These four distinct frequency bands of EEG signals show various power intensities during different sleep stages: wake (W), shallow sleep (N1 and N2), deep sleep or slow-wave sleep (N3), and REM. Each piece of EEG signal can be represented as a vector of four features, each indicating the band power of one of the four brain waves.

After obtaining the four-dimensional representation of EEG signals, we trained several simple classification models such as k-nearest neighbors (KNN), decision tree (TD), and linear discriminant analysis (LDA). However, the results were not satisfactory, with a final best testing accuracy of about 60% from TD. Upon analyzing the training data, we identified the reason for the poor performance of these machine learning algorithms: different human subjects exhibit quite distinct data distribution in the feature space. Four examples of the data distributions from four human subjects are shown in Fig. 7 (plotted in the feature space of the band powers of the delta and alpha waves). Such significant data variations cause the learning model to perform well when applied to a single individual but fail to generalize when data from several human subjects are combined. Because of this, we propose the ensemble learning framework (Fig. 3) in this project to handle the problem of varying data distributions across a population of human subjects. The algorithm testing is still in progress.



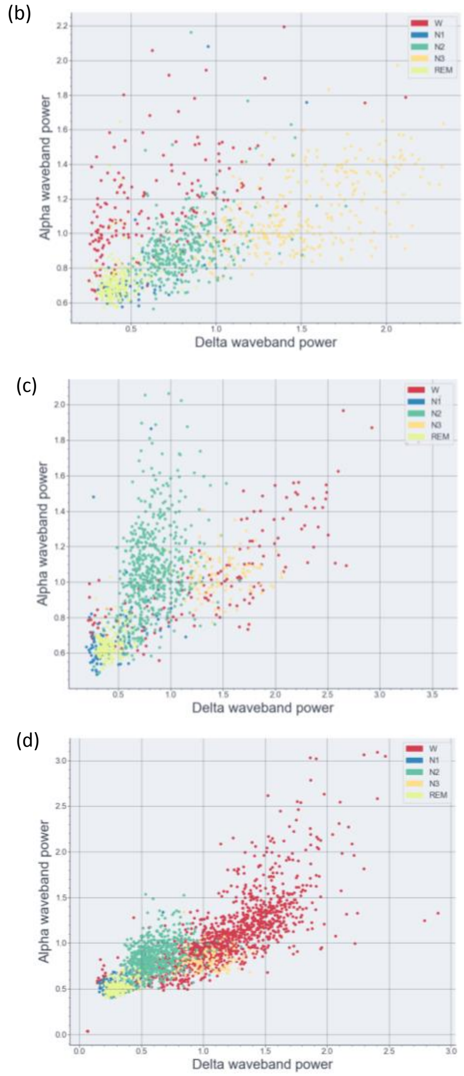


Fig. 7. Distributions of data from four human subjects (a)-(d) plotted in the feature space of the band powers of the delta and alpha waves. Points of different colors represent samples from different sleep stages: wake (W), N1, N2, N3, and REM.

V. Conclusion

This paper sketches out the idea of a wearable device that utilizes adaptive control and machine learning algorithms to analyze the EEG signals of the user and output electrical stimulation to improve relaxation and sleep. Some preliminary results demonstrate the potential of leveraging technology to improve sleep quality. The plan for the team is to complete the proposed design and continue researching the benefits of electronic stimulation on the brain by building and testing the device and by conducting human experiments and clinical studies.

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