In-ear Biosignal Recording System: A Wearable For Automatic Whole-night Sleep Staging

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ABSTRACT

In this work, we present a low-cost and light-weight wearable sensing system that can monitor bioelectrical signals generated by electrically active tissues across the brain, the eyes, and the facial muscles from *inside human ears*. Our work presents two key aspects of the sensing, which include the construction of electrodes and the extraction of these biosignals using a supervised non-negative matrix factorization learning algorithm. To illustrate the usefulness of the system, we developed an autonomous sleep staging system using the output of our proposed in-ear sensing system. We prototyped the device and evaluated its sleep stage classification performance on 8 participants for a period of 1 month. With 94% accuracy on average, the evaluation results show that our wearable sensing system is promising to monitor brain, eyes, and facial muscle signals with reasonable fidelity from human ear canals.

Keywords

in-ear wearable, biosignal, signal separation, sleep staging

1. INTRODUCTION

Sleeping allows muscles, bones, and organs to repair themselves and keeps our immune system healthy. It also helps consolidate human's brain development, learning, memory, and psychological health. However, sleep deprivation has become more serious than ever before due to many reasons. For example, the development of online and on-demand entertainment increases average screen time that consequently cuts down sleep time [24]. Hence, it becomes essential for sleep quality to be monitored so that not only itself is improved but also sleep-related diseases are detected and diagnosed in timely manner.

In hospital, polysomnography (PSG) system has long been used to evaluate sleep quality through sleep staging during the night. In order to determine sleep stages, electroencephalogram (EEG), electrooculography (EOG), and electromyography (EMG), among other sensing information, are measured. While PSG systems provide highly reliable sleep monitoring for clinical use, it has a number of drawbacks, making it modestly adopted anywhere other than clinical facility. The drawbacks include (1) the obtrusive attachment of a large number of wired sensors to the human body, (2) the need of professional installation and periodic checkup in a sleep laboratory, (3) the risk of losing contact between the sensor and the patient's body as patients move during sleep, and (4) the high cost of the system itself.

Growing at a fast pace, wearable and mobile devices are promising to address many problems that PSGs currently have. One approach is to infer sleep states by monitoring physical human activities using inertial measurement units (IMU), which are embedded in commercial off-the-shelf (COTS) wearable fitness trackers [10, 7, 15, 3]. Another approach is to keep track of the specific biosignals as a mimic of PSG system using electrodes attached on user's head and forehead [12, 9]. However, there are no existing low-cost sleep staging system that provides comfortable and accurate sleep quality monitoring.

In this work, we introduce a novel biosignal sensing system consisting of a wearable recorder to sense body's physiological signals from *inside human ears* and a signal separation algorithm to extract EEG, EOG, and EMG from the mixed signal recorded in the ear canal. There are many challenges in realizing such a system. First of all, the *long distance* between the sensor, which is inside the ear, and the sources of brain activities, eye movements, and muscle contractions makes the signal to noise ratio low. Second, the signals of interest (EEG, EOG, and EMG) are mixed into a

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WearSys'16, June 30 2016, Singapore, Singapore

DOI: http://dx.doi.org/10.1145/2935643.2935649

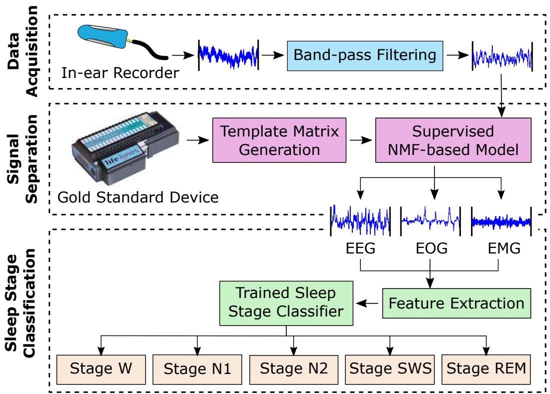


Figure 1: Overall architecture of an automatic sleep staging system that involves the proposed sensing system

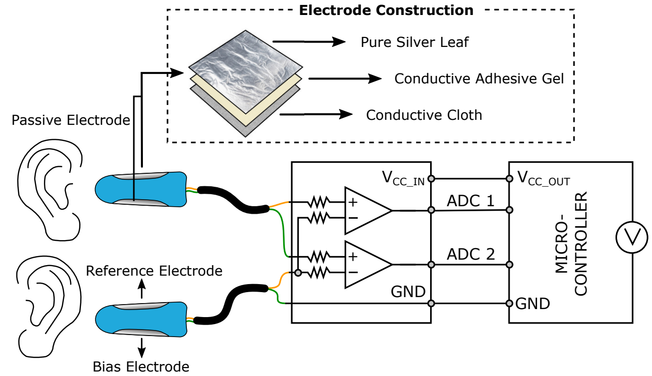


Figure 2: A simplified schematic of our in-ear biosignal recording system and a zoom-in of electrode structure

single-channel in-ear signal. Lastly, the individual physiological signals are widely different from person to person, making splitting them from the single channel difficult. To address these challenges, we propose an unique in-ear sensor design and develop a new signal separation algorithm. In particular, the wearable sensor is designed to be highly sensitive and resilient to body movement during sleep. The signal separation algorithm is able to learn source-specific prior knowledge and adapt to each user to obtain independent biosignals, minimizing loss of information. We integrate this wearable recording system with a sleep stage classification algorithm to build a practical automatic sleep staging system. Through a comprehensive set of experiments conducted in a sleep lab, the measurement provided by our wearable device is comparable to that provided by "gold standard" PSG. We make the following contributions in this work:

- Designing and prototyping a lightweight and inexpensive earplug-like recorder that is able to acquire good bioelectrical signals.
- Deriving and implementing a sleep staging algorithm for automatically classifying sleep stages at 30-second granularity.
- Deriving and implementing a signal separation algorithm for extracting EEG, EOG, and EMG signals from the mixed in-ear signal.

2. RELATED WORK

There are two states of consciousness, which are wakefulness and sleep. In accordance with the Rechtschaffen & Kales (R&K) [21] standard, in the sleep state, its normal process cyclically passes through four stages: drowsiness (N1), light sleep (N2), deep sleep (SWS), and rapid eye movement (REM) sleep. To identify the wakefulness and 4 sleep stages, a PSG needs a simultaneous recording of three fundamental physiological signals: EEG, EOG, and EMG [21]. As specified by Butkov in [4], in general, the measurement of EEG is most critical to precisely determine the sleep stages while the measurement of EOG and EMG is most necessary in differentiating REM sleep from other stages including the wakefulness state. By understanding the drawbacks of the PSG mentioned in Section 1 and the importance of those biosignals in assessing the sleep quality, we propose a light-weight, low-cost, precise, and easy-to-use wearable recording system that provides EEG, EOG, and EMG from the in-ear biosignal.

Alternatively, human ears have been seen as a promising location to record physiological signals and fundamental vital signs. In particular, Vollmer et al. [27] presented Biomon-HF sensor that has comparable abilities to detect sleep apnea by measuring photoplethysmography (PPG) from inside the ear. On the other hand, Sano et al. [23] proposed a wearable device in form of an earphone that can measure the pulse rate and EMG signal. Similarly, different earphone-shaped prototypes were developed to measure EOG signal for eye gaze detection [14]. In additional, many devices have been built to continuously record EEG signal on the complex outer surface of the ear [18] or in the ear canal such as an earphone cap [11], a hearing aid [13], and an earplug [8]. However, there have been still disadvantages such as instability, hardness, and the need of personalizing the earpiece in such existing works. In this paper, we propose a wearable recording system that can overcome those weaknesses. Also, our system is not limited to capturing only one specific biosignal in the ear canal, but three signals (EEG, EOG, and EMG) are collected. Finally, our recording system is integrated with a sleep stage classifier to automatically determine the sleep stages using the in-ear signal recorded on only one channel.

3. SYSTEM DESIGN

We begin this section by illustrating an overall architecture of the automatic sleep staging application using our wearable recording system. As shown in Figure 1, the system comprises three modules: (1) ***Data acquisition*** – By plugged into the ear canal, our wearable recorder acquires the biosignal that is then preprocessed to eliminate noise through different band-pass filters; (2) ***Signal separation*** – The preprocessed signal is next separated into EEG, EOG, and EMG through an adaptive separation method supervised by a spectral template matrix generated using a gold-standard device; and (3) ***Sleep stage classification*** – Finally, features are extracted from all three separated signals and input into a trained sleep staging model to obtain sleep stages at 30-second granularity. Below we elaborate on each of the aforementioned modules of our system pipeline.

3.1 In-ear signal acquisition

The most challenging tasks in this module are (1) to overcome the delicate structure of the human ear to achieve an efficient signal acquisition and (2) to have the device wearing comfortably inside the ear during the sleep. To fulfill these requirements, we build the wearable recorder in shape of an earplug with a pair of small and thin passive electrodes attached on its surface and propose its proper placement as shown in Figure 2. More specifically, our design focuses on three aspects:

+ ***Sensor material*** – To capture the biosignal with high fidelity inside the ear, it is important for the sensor to fit well with the ear canal. As personalizing a mold for each user's ear canal is costly and time-consuming, we propose the use of COTS foam earplug as an alternative. Its viscoelastic material enables the sensor to be placed easily by squeezing and reshape to its original form and size shortly later. Besides, its soft surface and lightweight property enable the sensor to be worn comfortably and safely in long term and provide a stable interface between the electrodes and the in-ear skin with minimum motion artifact;

+ ***Electrode construction*** – The electrode herein is made from a small piece of conductive silver cloth layered by pure and thin silver leaves many times on top. In details, because of its softness and strength, the cloth is chosen to make the sensor not harm the in-ear skin and not broken when plugged into the canal. However, due to the weave pattern of the fiber of this material, we propose to cover its surface using the silver leaf, which gives low and consistent surface-resistance as required; and

+ ***Electrode placement*** – To attain to the best signal acquisition, the placement of them should properly deployed in which we place the main electrode in one ear and the reference electrode in another ear. Due to their far distance, the voltage potential is increased that helps the signal to be measured more clearly.

3.2 Adaptive supervised signal separation

Constrained on the electrode placement explained in previous section, there can be only one biosignal obtained from inside the ear using our wearable. Moreover, as the position of the ear canal where the sensor is placed is relatively close to the sources of both the brain's signals and muscle movements, we consider that the in-ear signal captured is an actual mixture of EEG, EOG, and EMG signals and unwanted noise. Hence, we propose an algorithm that has an ability to separate those special signals from the mixed one, minimizing loss of information. To retrieve the original biosignals individually, the challenges in this work stems from the fact that (1) the number of channels that the sensor has (1 channel) is less than the number of signals of interest (3 signals) and (2) the overlapping and unstable properties of EEG, EOG, and EMG between people in different recordings in different domains. To address those challenges, we adopt a non-negative matrix factorization (NMF) model presented in [5] and further improve its performance through the source-specific prior knowledge extracted in a per-user training process. First, for a given mixed signal

$$\widetilde{X} = \sum_{i=1}^{3} w_i s_i + \epsilon \tag{1}$$

where s_i is one of EEG, EOG, and EMG with its corresponding weight w_i and ϵ is noise, the NMF model approximately splits the power spectrum X of $\widetilde{X}$ into a multiplication of two non-negative matrices H and W. Explicitly, H is an activation matrix involving activation information of each basis described in a spectral template matrix W. By choosing Itakura Saito (IS) divergence as a cost function, an approximation error between X and WH is minimized through multiplicative update rules of the following optimization problem

$$\{\hat{W}, \hat{H}\} = \underset{W,H \geq 0}{\arg\max} d(X|WH) \tag{2}$$

However, the quality of the separated signals can be degraded because of the conventional ill-posedness issue caused by the arbitrary initialization of W. Moreover, the variance of the biosignals from people to people in different sleeps also lead this model to a mismatch between the actual W and the decomposed W. Thus, a learning process is developed by taking the advantage of a single-class SVM [6] to initialize W from the ground-truth EEG, EOG, and EMG collected in its first use. As a result, our NMF-based separation algorithm is not only supervised to flexibly separate those signals but also adaptive to the variation of the signal.

3.3 Automatic sleep stage classification

Receiving the three separated signals output from our sensing system, the sleep staging algorithm provides sleep stage information based on the extraction of their special patterns. In details, the sleep stage classifier is composed of three components:

+ ***Feature extraction*** – To correctly identify suitable features extracted from each type of the signals, we rely on the knowledge studied from expert domain and existing features analyzed in research literature [16]. Briefly, it is observed that EEG signals provide brain waves possessing different chaotic parameters and different frequency patterns at each sleep stage. On the other hand, EOG and EMG lack frequency patterns but have large variation in amplitude, which is essential to magnify distinctions between Wake, REM, and N1 stages. Accordingly, the features that can powerfully distinguish five sleep stages are categorized into 3 groups: *temporal features* (average amplitude, variance, kurtosis, skewness, 75th percentil), 4 *spectral features* (absolute spectral powers, relative spectral powers, relative spectral ratio, spectral edge frequency), and 2 *non-linear features* (fractal dimension, entropy).

+ ***Feature selection*** – In fact, the performance of a classification algorithm can be degraded when many features are used in combination. As a result, in this component, a procedure called *Forward Selection* (FSP) is adopted to manage

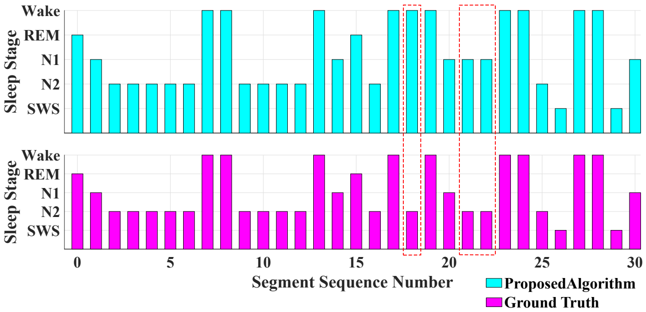


Figure 3: A hypnogram of 20-minute data illustrating the classification result done by the proposed sleep staging system (top) and compared with the ground truth (bottom). Its misclassification is marked by red dashed rectangles.

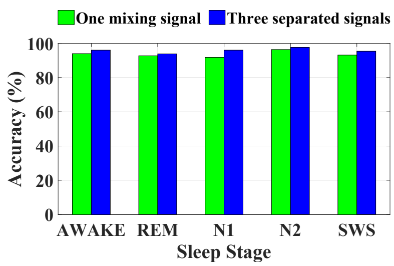


Figure 4: The accuracy of sleep staging using separated EEG, EOG, and EMG as inputs (blue) compared with the accuracy achieved when using the mixed signal (green)

this issue by identifying the most effective combination of features extracted previously. In addition, a weight to each selected feature is assigned and adjusted based on the classification error computed in a training process.

+ ***Sleep stage classification*** – To classify every 30-second segment of the sleep data into different sleep stages, an ensemble learning method is deployed. In this work, the *Random Forest* model with 25 decision trees is derived and trained using the set of previously selected optimal features. This classification method is chosen due to its computational efficiency and accurate prediction of categorical values for the identification of sleep stages [25]. Also, this model can overcome the problem of overfitting in high dimensional data [1].

4. EVALUATION

In this section, the performance of the proposed wearable recording system is generally evaluated through the efficiency of the sleep staging system. Hence, we first present the performance of the sleep staging module in a long-term sleep study. Then we prove the simultaneous occurrence of EEG, EOG, and EMG in the mixed in-ear signal through a set of hardware evaluations. Finally, we illustrate our signal separation algorithm possesses the capability of extracting those individual signals with minimum loss of information.

4.1 Experimental design

To validate our sleep staging system, we conducted a 38-hour sleep study on 8 graduate students (3 females, 5 males) with an average age of 25 in a sleep lab. To gather both in-ear signals and ground truth, our wearable recorder was plugged into their ear canals while a FDA-approved portable PSG was hooked up around their head. To sample and digitize the in-ear signal, our sensor was connected to an open-source brain-computer interface (OpenBCI) board [19] configured at 2kHz with a gain of 24. On the other hand, the ground truth was collected using Trackit Mark III supported by LifeLines Neurodiagnostic Systems Inc. [26] configured at 256Hz with a 0.1–70Hz pre-filter. After that, the Polysmith software [20] was run to score the ground-truth signals including 6-channel EEG, 2-channel EOG, and 2-channel EMG into different sleep stages at every 30-second segment.

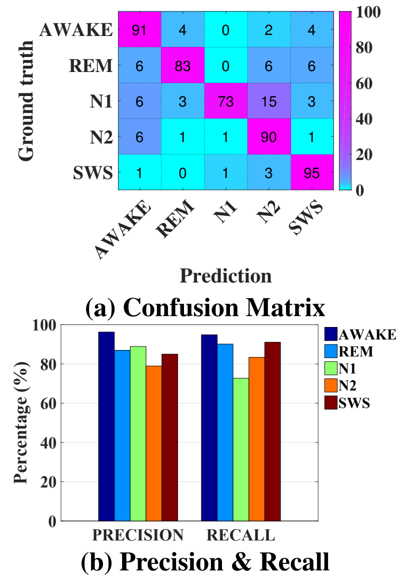
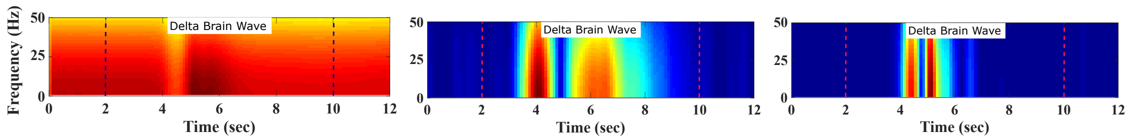


Figure 5: The confusion matrix, precision, and recall of sleep staging using separated EEG, EOG, and EMG as inputs

4.2 Sleep stage classification evaluation

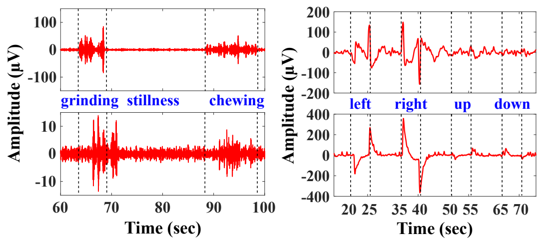
The performance of our proposed sleep staging algorithm is shown visually in the form of a hypnogram and numerically by computing the accuracy, recall, and precision values.

In details, Figure 3 demonstrates two hypnograms plotting the sleep stages of a 15-minute data obtained by our classifier (in blue) compared to the ground truth (in pink). In this figure, we observe that the dynamics of these hypnograms were almost well maintained. In another way, Figure 4 shows that our end-to-end system can achieve 94% accuracy of sleep staging on average. In this figure, the effectiveness of our signal separation algorithm is also proved by comparing the performance in two different scenarios. Specifically, in the first scenario, only the mixed in-ear signal was used to train and test the system. Otherwise, the second scenario used separated EEG, EOG, and EMG signals as inputs for training and testing the system. Thus, having a higher accuracy in the later case can be explained by that our separation algorithm is able to eliminate the noise



(a) Mixed in-ear signal **(b) Ground-truth EEG signal** **(c) Separated EEG signal**

Figure 6: An illustration of the signal quality after applying the adaptive supervised NMF-based separation algorithm to a 12-second signal captured during the stage SWS



(a) Muscle activities **(b) Eye movements**

Figure 7: The detection of muscle contractions (i.e. teeth grinding and chewing) and eye movements in 4 different directions made by our in-ear wearable device (top) and the gold standard device at its EMG and EOG channels, respectively (bottom)

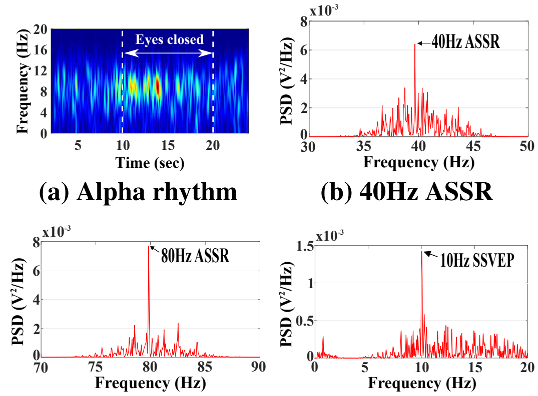
included in the mixed signal from the individual ones. As a result, the extracted features contain more discriminant information. Finally, the confusion matrix and the precision and recall achieved when using the optimal set of features are presented in Figure 5a and Figure 5b, respectively.

4.3 Signal acquisition evaluation

The quality of the in-ear signals obtained by the proposed wearable recorder has been evaluated by comparing them with the corresponding signals captured by the gold standard device. Specifically, we first evaluated the capability of the proposed in-ear device of recording EOG and EMG signals by detecting the occurrence of eye movements and muscle activities, respectively, in the in-ear signal. Figure 7a shows that our in-ear device can clearly capture specific facial muscle contractions, which are grinding and chewing, compared to the gold standard device at its EMG channel. On the other hand, although the amplitude of the in-ear signal was smaller than the one captured by the gold standard device, Figure 7b shows that our sensor was able to clearly and similarly capture the left and right eye movements. After that, we verified its capability of recording actual EEG signals by conducting the following BCI experiments:

+ ***Alpha attenuation response (AAR)*** - Alpha waves are brain waves specified within the frequency range of 8–13Hz [2] and generated during eye closing. Our wearable device could capture the alpha rhythms from inside the ear as shown in Figure 8a. However, we observed that the signal was not very clear. This can be due to the fact that the Alpha waves are produced in the frontal lobe that is far from the location of ear canals.

+ ***Auditory steady-state response (ASSR)*** - This paradigm measures the EEG responses to amplitude modulated auditory stimuli within a specific frequency range [22]. In our experiments, we applied auditory stimuli at two frequencies 40Hz and 80Hz. The experimental results produced a sharp and dominant peak at 40Hz and 80Hz, respectively, as we expected. Figure 8b and Figure 8c demonstrate the ability of the proposed in-ear wearable device to detect those two responses.



(a) Alpha rhythm **(b) 40Hz ASSR**

(c) 80Hz ASSR **(d) 10Hz SSVEP**

Figure 8: The EEG paradigms' results obtained from the in-ear signals recorded by our proposed wearable device

+ ***Steady-state visually evoked potential (SSVEP)*** - Similar to AASR, this experiment measures the brain wave responses to visual stimuli at specific frequencies [17]. Following that, we stimulated the brain wave responses by doing blinking stimuli at the frequency of 10Hz. As a result, the SSVEP response peak at that frequency was able to be recorded and is displayed in Figure 8d.

4.4 Signal separation evaluation

From the above evaluations, we did prove the occurrence of all EEG, EOG, and EMG signals in the single-channel in-ear signal. We now validate the quality of the separated signals by showing that the signal separation algorithm we propose can successfully keep their intrinsic characteristics when extracted from the mixed signal. Specifically, in Figure 6, we analyzed a 12-second signal captured by our wearable recorder during the SWS stage as reported by the gold standard device. Based on medical knowledge, we know that the Delta brain wave in the range of less than 4Hz should appear in this EEG signal. Hence, we applied a 0.1–5Hz band-pass filter into three different EEG signals captured in that period of time, which are (1) the mixed in-ear signal, (2) the ground-truth signal, and (3) the separated signal and then analyzed their spectrogram as shown in Figure 6a, 6b, 6c, respectively. Analyzing this figure, the short appearance of the Delta brain wave in Figure 6c can be explained by the fact that the location where our wearable placed is far from the source of the signal. As a result, it is difficult for our device to capture the signal when its amplitude is reduced. Moreover, we see that the spectrogram in Figure 6a is completely different from the two shown in Figure 6b and 6c. We can explain it using the fact that there exist other signals that are in the same frequency range of the Delta brain wave in the mixed signal excluding the EEG signal.

5. CONCLUSIONS

In this paper, we proposed a biosignal recording system placed inside the human ears for sensing EEG, EOG, and EMG signals. By using a small number of highly sensitive, soft, and thin electrodes, the wearable recorder shows its comfort as wearing earplugs during sleep. We also deployed an adaptive supervised algorithm for extracting those individual signals, which are then input into our implemented sleep staging system. We have experimentally evaluated our in-ear wearable system through different hardware evaluations and a 38-hour sleep study. We found its potential in term of good signal acquisition and sleep staging accuracy when compared to the existing gold-standard sleep monitoring systems (e.g. PSG). Based on its promising results and desirable properties of low cost, easy to use, and lightweight to wear, we will explore the possibility of applying this wearable system to various health diagnosis, health monitoring, and biomedical research.

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