**Anh Nguyen, Raghda Alqurashi, Zohreh Raghebi, Farnoush Banaei-Kashani, Ann C. Halbower and Tam Vu** *University of Colorado Boulder*

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# LIBS: A Lightweight and Inexpensive In-Ear Sensing System for Automatic Whole-Night Sleep Stage Monitoring

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Sleep is an essential mechanism contributing to human physical and mental well-being. Lack of high-quality sleep can affect overall health with serious medical issues, such as diabetes, heart disease, and obesity, among others [1]. To assess sleep quality, the patient usually undergoes a clinical sleep study [2] in which a polysomnography (PSG) [3] acquires biosignals reflecting electrical activities of their brain (EEG), eyes (EOG), and muscles (EMG). While PSG provides reliable results, it is uncomfortable, time-consuming, and expensive due to the obtrusive attachment of many wired sensors to the patient's head, face, and the whole body; the risk of losing sensor contact caused by body movements; and the need of a well-trained expert to score the recorded data.

In this paper, we introduce LIBS, a wearable sensing system, that can capture the biosignals representing electrical activities of the brain, eyes, and muscles separately from inside human ears for accurate sleep staging. As comfortable as wearing a pair of earbuds while listening to music, LIBS is cost-effectively designed to have very few passive electrodes placed in small-size ear canals for measuring the biosignals of interest. Due to the unique structure of the outer ear, the in-ear biosignal obtained by LIBS is a mixture of EEG, EOG, and EMG and unwanted noise, which is then split without loss of physiological characteristics using an adaptive signal separation model. Finally, LIBS applies a classification model to score every 30-second sleep data into its appropriate sleep stage.

Realizing such an in-ear biosensing system leads to three key challenges. First, the signal acquired from inside the ear is a mixture of multiple signals of interest and noise. It is challenging yet necessary to distil useful signals including EEG, EOG, and EMG signals from the mixture. It is difficult because the signals have overlapping temporal and spectral characteristics and their sources can be simultaneously activated. Secondly, the biosignals acquired vary across people and across recordings due to the displacement of electrodes in different hookups and the difference of physiological conditions among individuals. Thus, making the separation algorithm robust even with the presence of the variance becomes a significant hurdle. Last but not least, the sources of low-amplitude brain, eye, and facial muscle signals are far from the location where the electrodes are placed as shown in Figure 1. Hence, it is challenging to develop sensors capable of recording them from afar while maintaining a high comfort level to its users who wear them during whole-night sleep.

To address the aforementioned challenges, we make the following contributions: (1) We augment a low-cost off-the-shelf foam-based earplug sensor with a novel design of highly sensitive electrodes made of a combination of thin, soft, and highly conductive materials. Thus, LIBS itself is a lightweight, low-cost, easily placed device that rests comfortably and safely inside human ears to provide high fidelity and long-term continuous measurement of voltage potential of biosignals. (2) We derive and implement a single-channel signal separation model, which can decompose EEG, EOG, and EMG signals from the mixed in-ear signals by integrating a learning process based on their physiologic and electrical properties. (3) We derive and implement a complete sleep-staging system with the granularity of a 30-second epoch.

## LIGHTWEIGHT BIOELECTRICAL SENSING SYSTEM (LIBS) DESIGN

Human beings pass through two states of consciousness: wakefulness and sleep with four distinct sub-stages of N1, N2, N3, and REM [4] occurring in repeated cycles. In clinical sleep study facilities, polysomnography (PSG) is currently used as a gold standard to identify sleep stages and examine sleep architecture to study the quantity and quality of sleep by simultaneously evaluating brain activities, eye movements, and muscle contractions [5]. The relationship between the sleep stages and EEG, EOG, and EMG signals is illustrated in detail in [6].

Understanding the significance of EEG, EOG, and EMG in health care, specifically for sleep assessment, and the drawbacks of PSGs, LIBS was designed to be a long-term monitoring system that can automatically determine different stages of sleep using EEG, EOG, and EMG signals separated from the single-channel biosignal captured in the ear canal during sleep. The workflow of LIBS, as illustrated in Figure 2, consists of three primary modules:

**(i) Data acquisition and preprocessing:** This module tackles the hardware challenges of (1) the small uneven area inside the human ear and its easy deformability under jaw movements (2) the microvolt level of the biosignals, and (3) comfortable, harmless, and self-wearing to users. Thus, we made a design of wearable deformable earplugs consisting of sensitive electrodes made of thin, soft, and highly conductive materials over a viscoelastic material, shown in Figure 2 (left). Moreover, we increase the distance between the main and the reference electrodes to further improve the signal potential. Accordingly, LIBS can sense weak in-ear biosignals and then preprocess to eliminate possible interferences (e.g., movement artifacts, noises, etc.).

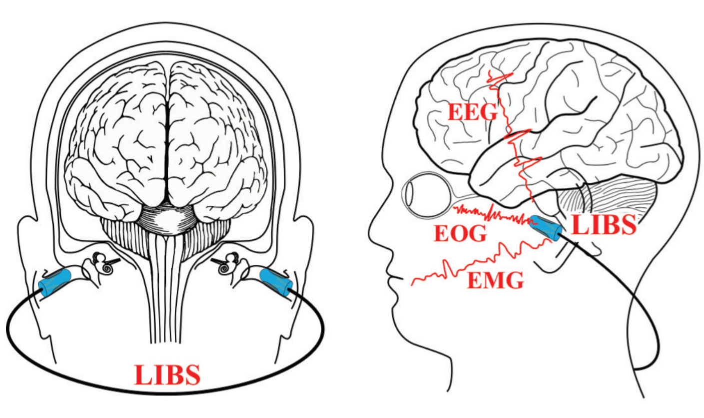



**FIGURE 1.** Conceptual illustration of LIBS and its relative position to the sources of three biosignals of interest: EEG, EMG, and EOG.

**(ii) In-ear signal separation:** This module overcomes the signal challenges of (1) overlapped characteristics of three biosignals in time and frequency domains (2) a random activation of the signal sources, and (3) their variation across people in different recordings. We, thus, elaborate a non-negative matrix factorization (NMF)-based model [7, 8] that can separate the single-channel in-ear mixture into EEG, EOG, and EMG signals with high similarity to the ground truth given by PSGs. Specifically, the algorithm learns patterns of those biosignals in advance to attain their individual spectral template and then adapt to the variation between people through a deformation step. Therefore, the built model slightly alters the signal templates by themselves to return the best fit of the expected biosignals.

**(iii) Sleep stage classification:** This module handles the classification challenge of similar characteristics of the biosignals shared in some sleep stages. We, thus, deploy a random forest classifier [9] trained with discriminative features extracted from the separated in-ear EEG, EOG, and EMG to automatically score the sleep into different stages, namely Awake state, N1, N2, N3, and Rapid Eye Movement (REM).

## IMPLEMENTATION

**Sensor material:** We selected a sound block foam earplug due to its soft elastic property that enables the sensor to be squeezed or twisted easily under the strain to insert into the ear and then reshape to its original form shortly. Furthermore, the foam earplug also provides a comfortable and good fit for the ear, supplies a stable skin-electrode contact, eliminates the sensor personalization regardless of ear canal size, and blocks out noise, hence improving the sleep.

**Electrode construction and placement:** We designed the electrodes in a 10 x 7mm oval shape. Also, our experiment on different conductive materials led us to the choice of conductive fabric due to its softness, and further stabilized the resistance between the fabric electrode and the outer layer of the skin by coating its surface with three layers of a pure and thin silver leaf. Ultimately, we placed the main and reference electrodes inside two different ears, hence intensifying the signal strength. Finally, shielded wires

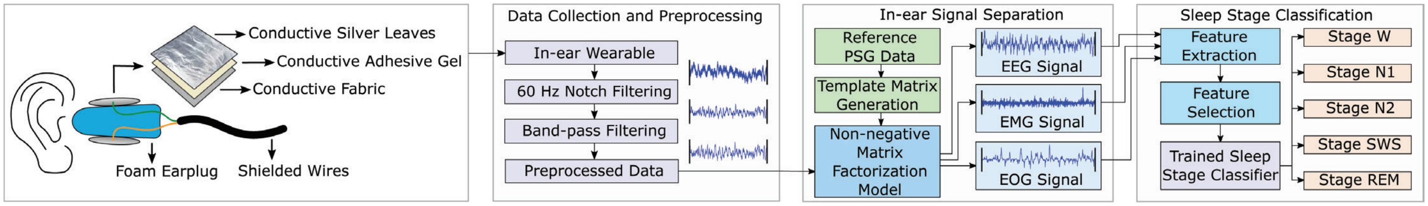



**FIGURE 2.** LIBS's architecture (left) and operation workflow for automatic whole-night sleep stage monitoring.

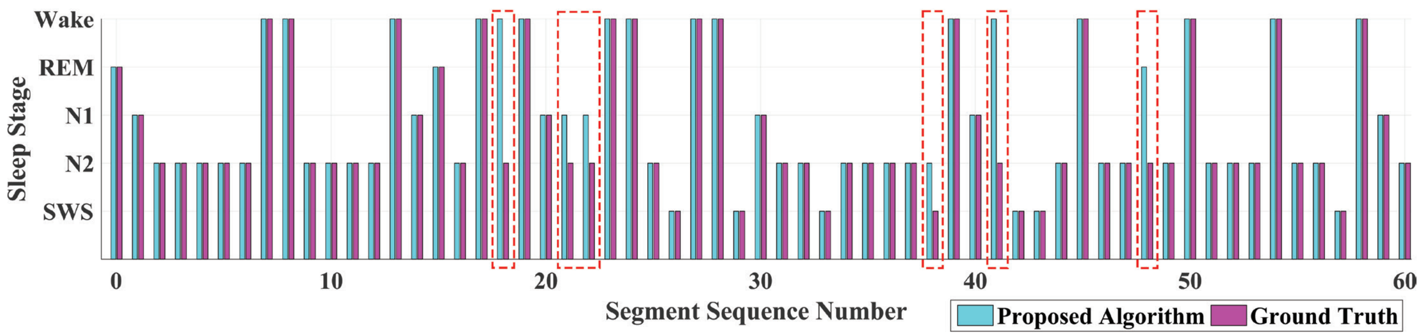



**FIGURE 3.** A hypnogram of 30-minute data resulted by LIBS. Sleep staging done using LIBS (light blue) is compared with the ground truth from PSG (dark pink). The misclassification of our algorithm is marked by red dashed rectangles.

were used to prevent external noise added to the recorded in-ear signal transferred from the electrode to a microcontroller.

**LIBS microcontroller:** We use a OpenBCI board named Cyton [10] to sample, digitize, and store the in-ear biosignal in an on-board mini-SD card. The board is 6V-battery supplied and configured at a 2kHz sampling rate and a 24x gain.

## EVALUATION

We conducted a 38-hour sleep experiment with eight graduate students and various standard brain-computer interface (BCI) experiments to evaluate the performance of LIBS in different aspects. For all studies and experiments, the participants were asked to plug LIBS into their ears and have a conventional PSG (i.e., Trackit Mark III [11] at 256Hz sampling rate) hook-up around their head simultaneously.

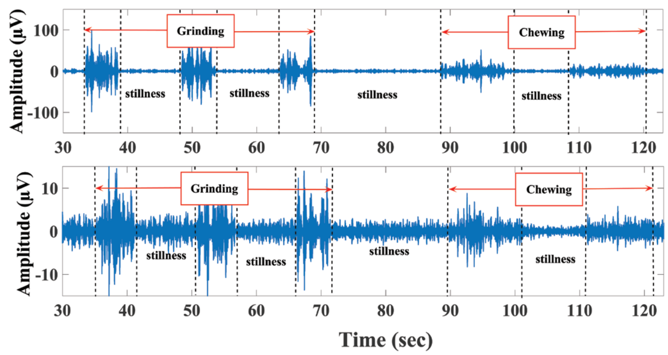
**Sleep stage classification performance:** We evaluate our proposed random forest classifier for determining the sleep stages corresponding to every 30-second data epoch recorded and separated using LIBS. Particularly, Figure 3 exhibits the sleep staging result using the in-ear separate brain, eye, and muscle signals in comparison to the hypnogram scored by PolySmith [12] using the groundtruth PSG signal. From this figure, it can be observed that the dynamics of our hypnogram is almost completely maintained in the predicted scores. Consequently, our end-to-end system can achieve 95% accuracy in sleep staging on average.

**In-ear signal validation:** We first assess the quality of the original in-ear signal acquired by LIBS regarding its capability to capture events reflecting eye movements and facial muscle contractions. Figure 4a, in detail, shows that LIBS can clearly record the grinding and chewing activities in the EMG signal (top) compared to the ground truth signal captured by the gold-standard device (bottom). Similarly, the EOG signal displaying the left and right eye movements can be distinguished in Figure 4b.

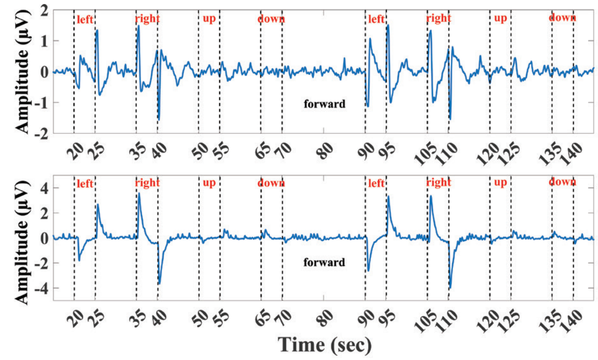
Finally, the appearance of the EEG signal is demonstrated together with the performance of our proposed signal separation algorithm. Specifically, spectrograms shown in Figure 4c (top) proves that the separation model we propose has an ability to split the signals completely from the mixed one without loss of their specific characteristics, which is the delta wave in a frequency range lower than 4Hz, compared to the groundtruth EEG signal captured on the scalp shown in Figure 4c (bottom). We refer the readers to [6] for more detailed validations of signal acquisition and separation, their comparison with the signals recorded by the gold-standard device (i.e., PSG), and our user study.

## CONCLUSION

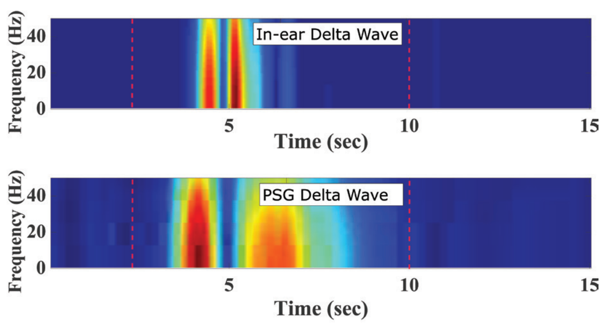
In this work, we have presented the design, implementation, and evaluation of LIBS, a wearable system that can sense the EEG, EOG, and EMG signals using a small number of electrodes placed inside users' ears. We have also introduced an adaptive NMF-based algorithm for separating the single-channel in-ear mixed signal into individual biosignals. Through our hardware prototype evaluation and user-study, we show that LIBS is comparable to the existing dedicated sleep assessment systems (e.g., PSG) in terms of sleep stages classification accuracy, while possessing many desirable




(a) Muscle activities in EMG




(b) Eye movements in EOG




(c) Delta wave in EEG

**FIGURE 4.** The detection of muscle activities (a), eye movements (b), and delta brain wave (c) from the in-ear biosignals recorded by LIBS (top) compared to the groundtruth signals (bottom).

properties, such as low cost, easy operation, and comfortable wearing during sleep. More than just automatic sleep staging, LIBS with its three individual biosignal outputs, has a potential to become a fundamental sensing device in divergent problems ranging from health to non-health and from mobility to non-mobility. ■

**Anh Nguyen** is a PhD candidate in the Department of Computer Science at University of Colorado Boulder. She received her MS at Chonnam National University in 2012 and BE at University of Science in 2009. Her primary research interests are in mobile systems, with emphasis on applying sensing techniques for mobile health care.

**Raghda Alqurashi** is currently a PhD candidate in Computer Science and Information Systems at University of Colorado Denver. She received her MS degree in Computer Science from the Department of Computer Science and Engineering at University of Colorado Denver in 2013. Her research interests include mobile computing, mobile health care solutions, sensors, and ubiquitous computing.

**Zohreh Raghebi** has been working toward her PhD degree at the Department of Computer Science and Engineering, University of Colorado Denver since 2015. She received her MS degree in Computer Science from the University of Tehran in 2014. Her current research interest includes big data mining and management on large scale graphs, and machine learning with an emphasis on biomedical and bioinformatics applications.

**Farnoush Banaei-Kashani** is an assistant professor at the Department of Computer Science and Engineering, University of Colorado Denver (UCD). He earned his PhD degree in Computer Science and MS degree in Electrical Engineering at the University of Southern California in 2007 and 2002, respectively. He is passionate about performing fundamental research toward building practical, large-scale, data-intensive systems, with particular interest in Data-driven Decision-making Systems (DDSs).

**Ann C. Halbower** is a pediatric pulmonologist in Aurora, Colorado, and is affiliated with multiple hospitals in the area, including Children's Hospital Colorado and University of Colorado Hospital. She received her medical degree from University of Massachusetts Medical School and has been in practice for more than 20 years.

**Tam Vu** is an assistant professor and directs Mobile and Networked Systems (MNS) Lab at University of Colorado Boulder, where his team works on building systems to improve pediatric health care practices. He designs and implements novel and practical cyber-physical systems to make physiological sensing less obtrusive at a lower cost. He received his PhD in Computer Science from WINLAB, Rutgers University in 2013, and his BS in Computer Science from Hanoi University of Technology in 2006.

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