# LIBS: A Low-cost In-Ear Bioelectrical Sensing Solution for Healthcare Applications

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#### **ABSTRACT**

Bioelectrical signals representing electrical activities of human brain, eyes, and facial muscles have found widespread use both as important inputs for critical medical issues and as an invisible communication pathway between human and external devices. However, existing techniques for measuring those biosignals require attaching electrodes on the face and do not come in handy sizes for daily usage. Additionally, no study has been capable of providing all three biosignals with high fidelity simultaneously. In this paper, we present a low-cost bioelectrical sensing system, called LIBS, that can robustly collect the biosignal of good quality from inside human ears and extract all those three fundamental biosignals without loss of information. The practicality of LIBS is shown through one real world scenario of a sleep quality monitoring system. Based on preliminary results, we further propose potential healthcare applications utilizing the sensor's outputs for our future research.

### **Keywords**

in-ear wearable, biosignals, signal separation, health care

#### 1. INTRODUCTION

For clinical environment, electroencephalography (EEG), electrooculography (EOG), and electromyography (EMG) are trusting methods to record fundamental neuronal electrical signals excited by brain activities, eye movements, and muscle contractions, respectively. To date, these signals are most often used not only in medical areas but also in brain-computer interface research. Measuring them, however, requires a set of electrodes attached on human body, which must be correctly done at clinical facilities. While these traditional approaches provide accurate measurement, they are cumbersome and expensive for daily life monitoring, cause

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discomfort for a person wearing them, and might risk a lead failure when the person moves.

Recent advances in wearable and mobile technologies have enabled promising hi-tech solutions to ease EEG, EOG, and EMG methods of a burden. For example, headphones [1, 5], headbands [15], and eye masks [8] have been built to capture the biosignals with a fewer number of electrodes. While the accuracy has been improved, these solutions still bring uncomfort and awkward visibility to users wearing them on forehead, scalp, or face for regular activities or sleep. There has been a remarkable research [3, 4, 6, 9, 10, 14] trying to find alternative places on the body to continuously and invisibly monitor the signals. However, they have not demonstrated the ability to possibly provide all three fundamental signals at a time with high fidelity and comfort for a low-cost, personal, and daily use.

Upon our prior work [12], we present LIBS as a lowcost in-ear bioelectrical sensing solution that brings convenient monitoring for daily use and provides good EEG, EOG, and EMG signals extracted from the single-channel biosignal recorded from the ear canals. Specifically, LIBS works with a wearable recorder built in the shape of ear buds embedding only two passive electrodes and placed comfortably inside the ear. Due to a special location of human ear canals, EEG, EOG, and EMG signals and unwanted noise are mixed together in the biosignal obtained by our in-ear device. Thus, LIBS takes the mixed in-ear signal and adopts a signal separation model to extract those three biosignals of interest without loss of information. In this paper, LIBS further proposes a novel solution to enhance the signal separation model capable of adaptively controlling the variability of the signals without a need of per-user learning process.

In this work, we have met following key challenges:

- + Delicate structure of ears and low amplitude signals: Analyzing an anatomy of human head results that sources of brain activities, eye movements, and muscle contractions are far away from the in-ear electrodes making the signal-to-noise ratio low. On the other hand, the ear canals have a small uneven volume and are easily deformed by muscle movements. Therefore, assuring an ability to achieve an *efficient signal acquisition from far distance* challenges *LIBS* to thoroughly design its sensing system.
- + Only one recording channels and overlapping signals: Recording the biosignal cannot avoid a problem of mixing

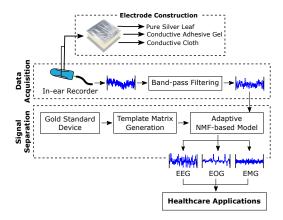


Figure 1: Overall architecture of LIBS

signals since their sources are possibly activated simultaneously. So, the second challenge of *LIBS* emanates from the necessary of retrieving individual EEG, EOG, and EMG signals while the number of recorded channels is fewer than the number of signals of interest, whose amplitude and frequency are highly overlapped.

+ Variability of signals across people in separate sleep recordings: The biosignals are widely divergent from people to people due to their personal physiological conditions. They are also varied in different signal acquisitions because of the displacement of electrodes in distinct device hookups. As a result, avoiding per-user training phase becomes a great challenge of *LIBS* to develop a robustly adaptive signal separation algorithm.

#### 2. LIBS DESIGN

In this work, *LIBS* is designed to automatically capture the bioelectrical signal in the ear canal and then precisely extract individual EEG, EOG, and EMG signals from that single-channel in-ear signal. As shown in Figure 1, *LIBS* is composed of two main modules:

**Data acquisition** – To overcome the first challenge of collecting the low amplitude biosignal inside the delicate-structure ear, our wearable recorder is built from a *foam earplug* to make it fit well within the ear canal without personalization and small pieces of *conductive silver cloth* to increase the responsiveness of electrodes. Different from [3], we further (1) cover the electrodes with many pure and thin *silver leaves* on top to achieve low and consistent surface-resistance for the electrodes and (2) place the main electrode in one ear and the reference electrode in another ear to amplify the signals. Due to the measurement in voltage potential, creating a far distance between these electrodes is very helpful. Hence, our device is able to acquire the good single-channel in-ear biosignal that is later passed through different band-pass filters to eliminate noise.

**Signal separation** – To solve the second challenge of having the fewer number of recording channels than the number of signals of interest, we develop the signal separation model from a *non-negative matrix factorization* (NMF) technique [2]. Specifically, this technique tries to solve an optimization problem of decomposing the power spectrum X of the in-ear signal into a multiplication of two distinct non-

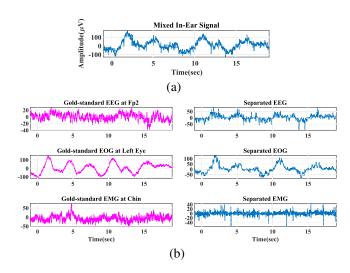


Figure 2: A comparison of EEG, EOG, and EMG signals (b) recorded by the gold-standard device (pink) and extracted by our signal separation algorithm (blue) using the single-channel in-ear signal (a) during stage N1 of a real sleep study

negative matrices

$$X \simeq WH$$
 (1)

where W represents a spectral template of three signals and H represents activation information of each basis described in the template W. Different from [2], a learning process is further studied to build a fixed spectral template matrix corresponding to each EEG, EOG, and EMG from the ground-truth data, which helps deal with their overlapping and unstable properties. To handle the third challenge of biosignal variability, an idea of group analysis [7] is adopted to seek common patterns that reflect the variability from user to user studied from the training set of ground-truth data with a modification of Equation 1 as following

$$X \simeq W_C H_C + W_I H_I \tag{2}$$

where  $W_C$ ,  $H_C$ ,  $W_I$ , and  $H_I$  are common sparse and individual template and activation matrices, respectively.

#### 3. CASE STUDY: SLEEP STAGING

We preliminarily evaluated LIBS in its practicality, usability, and accuracy through a healthcare application. In this scenario, a user wears a pair of earplugs integrated with LIBS to automatically record his in-ear biosignal while sleeping. The in-ear mixture is then preprocessed and separated into EEG, EOG, and EMG signals that are later applied into a classification model to automatically determine sleep stages at 30-second granularity. The hardware setup includes the ear-worn recorder connecting to an OpenBCI board [13] configured at a sampling rate of 2000 Hz and a gain of 24. The recorded signal is currently written to a SD card plugged directly to the board for storage and processed by Matlab. Simultaneously, we hook up the user with a portable PSG Trackit Mark III [16] to collect groundtruth EEG, EOG, and EMG signals during sleep and then use the POLYSMITH<sup>TM</sup> program to provide the groundtruth sleep stages for both

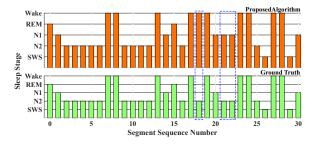


Figure 3: A hypnogram of 15-min data showing the sleep staging result with the three input signals given by *LIBS* (top) and compared to the ground truth (bottom). Blue dashed rectangles are used to mark its misclassification.

training and evaluating *LIBS* when necessary. As shown in Figure 2, our signal separation algorithm integrated in *LIBS* was supervised well to be able to extract EEG, EOG, and EMG signals with high quality and similar shape compared to the corresponding signals captured by the gold-standard device. On the other hand, as shown in Figure 3, we observe that the dynamics of the hypnogram was almost well maintained in case of our end-to-end system. Hence, we see opportunities provided to reliably develop healthcare applications using the biosignals output by *LIBS*.

#### 4. FUTURE RESEARCH

In health care, EEG, EOG, and EMG provide a lot of important information of human brain, eyes, and muscles. Consequently, achieving those bisignals from the mixed in-ear signal by *LIBS* provides very informative inputs to health-care applications. In this section, our future research into the use of LIBS' outputs and its challenges are discussed.

- + Sleep quality monitoring: Evaluating sleep quality always requires a precise computation of the duration of different sleep stages identified through a simultaneous recording of those three fundamental signals. In this application, the challenge is to provide suitable features extracted from the biosignals and then decide the most effective combination of the features in a training process to maximize the distinction between all sleep stages.
- + Sleep environment controlling: Environmental factors (e.g. light intensity, room temperature, air humidity, air pressure, and ambient sounds) can be an essential reason for interrupted and poor sleep quality on human [11]. In this scenario, EEG, EOG, and EMG output from *LIBS* can represent the user's sleep quality. The challenge is to develop a causality model that is capable of investigating the correlation between environmental variations and the biosignals to further provide suggestions for improving sleep quality.
- + Brain-related disease diagnosis: EEG is an essential component in the evaluation of brain-related diseases (e.g. epilepsy, sleep disorders, etc.). Most of such the diseases are caused by a disruption in the way the brain is working. Hence, the challenge of this application is to discover special patterns defining their pre-occurrence state in the activity of brain cells showing in EEG in real time.
- + Sudden infant death syndrome (SIDS): SIDS is defined as a sudden unexplained death of a child less than one

year of age. Recently, a prevention of it can be done by monitoring changes in their EEG, EOG, and EMG. However, using *LIBS* in this situation is very challenging since (1) the overall volume of their ear canal and the amplitude of their biosignals is significantly small and (2) the patterns of their biosignals differ from those of adults. Those challenges require *LIBS* to have a significant improvement on the design of the wearable recorder as well as a novel signal separation algorithm that can adapt well in case of babies.

+ Autonomous audio steering for hearing aids: In this application, the purpose is to help people with hearing impairment improve speech understand in background noise by silently controlling their hearing aid to only amplify the sound source coming from the direction of interest (i.e. from left or right ears). In this application, the challenge is to automatically detect which direction of the sound source the wearer is focusing on by only analyzing the change of EEG signal.

#### 5. CONCLUSIONS

A low-cost in-ear bioelectrical sensing system to capturing good EEG, EOG, and EMG signals with high comfort has been presented. Our preliminary implementation of classifying different sleep stages during sleep demonstrated the feasibility of developing healthcare applications using fundamental biosignals sensed in human ear canals and extracted from the single-channel in-ear biosignal. Our in-ear sensing solution also offered potential advantages of long-term, light-weight, and reliable usability that asks for a further exploratory step toward a professional design of the earplug-like wearable device and a novel signal separation algorithm to flexibly adapt the variability of the biosignals across people and across recordings.

## **6. REFERENCES**[1] Aware. https://goo.gl/eh48HA. Accessed: 08/15/2016.

- [2] C. Damon et al. Non-negative matrix factorization for single-channel EEG artifact rejection. In *IEEE ICASSP*, 2013.
- [3] V. Goverdovsky et al. In-ear EEG from viscoelastic generic earpieces: Robust and unobtrusive 24/7 monitoring. *IEEE Sensors Journal*, 16(1), 2016.
- [4] W. Gu et al. InEar BioFeedController: A Headset For Hands-Free And Eyes-Free Interaction With Mobile Devices. In ACM CHI, 2013.
- [5] KOKOON. https://kokoon.io/. Accessed: 08/15/2016.
- [6] A. Kulkarni et al. Soft, curved electrode systems capable of integration on the auricle as a persistent brain-computer interface. In Proc. of the National Academy of Sciences, 2015.
- [7] A. Lefevre et al. Itakura-Saito nonnegative matrix factorization with group sparsity. In *IEEE ICASSP*, 2011.
- [8] S. F. Liang et al. Development of an EOG-Based Automatic Sleep-Monitoring Eye Mask. 2015.
- [9] H. Manabe et al. Conductive rubber electrodes for earphone-based eye gesture input interface. *Pers Ubiquit Comput*, 19, 2015.
- [10] N. Merrill et al. Classifying Mental Gestures with In-Ear EEG. In IEEE BSN, 2016.
- [11] A. Nguyen et al. mSleepWatcher: Why didn't I sleep well? In ISSAT MCSE, 2015.
- [12] A. Nguyen et al. In-ear Biosignal Recording System: A Wearable for Automatic Whole-night Sleep Staging. In ACM WearSys, 2016.
- [13] OpenBCI. http://openbci.com/. Accessed: 08/15/2016.
- [14] A. Sano et al. Applications using Earphone with Biosignal Sensors. In *Human Interface Society Meeting*, 2010.
- [15] Sleep Shepherd. http://sleepshepherd.com/. Accessed: 08/15/2016.
- [16] Trackit. https://www.lifelinesneuro.com/. Accessed: 08/15/2016.