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Drowsiness Detection with Wireless, User-Generic, Dry Electrode Ear EEG

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***Abstract*— Drowsiness monitoring can reduce workplace and driving accidents. To enable a discreet device for drowsiness monitoring and detection, this work presents a drowsiness user-study with an in-ear EEG system, which uses two user-generic, dry electrode earpieces and a wireless interface for streaming data. Twenty-one drowsiness trials were recorded across five human users and drowsiness detection was implemented with three classifier models: logistic regression, support vector machine (SVM), and random forest. To estimate drowsiness detection performance across usage scenarios, these classifiers were validated with user-specific, leave-one-trial-out, and leave-one-user-out training. To our knowledge, this is the first wireless, multi-channel, dry electrode in-ear EEG to be used for drowsiness monitoring. With user-specific training, a SVM achieved a detection accuracy of 95.9%. When evaluating a never-before-seen user, a similar SVM achieved a 94.5% accuracy, comparable to the best performing state-of-the-art wet electrode in-ear and scalp EEG systems.**

***Index Terms*— Dry electrodes, ear EEG, user-generic, classification, neural recording, drowsiness**

I. INTRODUCTION

Drowsiness has been linked to a decline in productivity, response-time, and cognitive performance. When cognition is impaired, drivers, pilots, security guards, and nuclear facility personnel are all at increased risk of errors, occupational accidents, and bodily harm. For instance, fatigued drivers account for up to 18% of vehicle accidents [1].

To prevent accidents, drowsiness monitoring and detection systems have been implemented using camera-based eye tracking, steering trajectory sensors, and physiological recording devices. Camera-based systems rely on tracking the percentage of time the eyelids are closed, making them susceptible to obstructions. Steering trajectory sensors track steering wheel movement, limiting their use to vehicles and making them vulnerable to noise from rough roads. User-centered recording modalities including electrocardiography, electrooculography, and electroencephalography (EEG) are becoming increasingly popular since they may be worn by a user in varying workplace environments. Of these three sensing paradigms, EEG tends to achieve the highest drowsiness detection accuracy [2].

EEG is a safe, non-invasive method of monitoring the brain's electrical activity from the scalp. In a clinical setting, large electrode arrays are used to monitor neurological disorders related to epilepsy and sleep with high spatial resolution. Compact EEG systems are used in ambulatory research settings to monitor spontaneous and evoked neural rhythms related to attention and environmental stimuli. Both types of systems generally require a technician to abrasively clean the skin and place wet electrodes. This skin preparation introduces the risk of skin lesions, and the recorded signal to noise ratio (SNR) degrades as the wet electrodes dry out [3]. To enable longer recordings, wearable, dry electrode scalp EEG systems have been developed, but require bulky headsets [4]. Recently, multi-channel EEG has been recorded from inside the ear with user-generic, dry electrode earpieces [5]. While in-ear EEG does not provide the same spatial covering as scalp EEG, it can discreetly record large-scale neural signals including alpha and gamma oscillations.

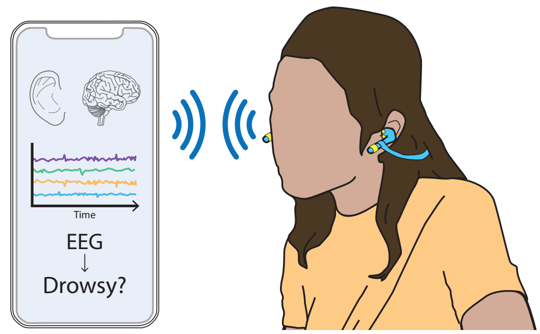

Fig. 1. Envisioned Ear EEG device discreetly recording EEG from inside the ear canal and performing drowsiness detection for a user.

To our knowledge, all in-ear EEG drowsiness detection systems use low-channel counts and wet electrodes [6][7][8]. To make these systems user-friendly, it is ideal to have a user-generic, dry electrode system (Fig. 1). To this effect, this paper presents a wireless, user-generic, dry electrode in-ear EEG (Ear EEG) drowsiness detection system with accuracy comparable to state-of-the-art wet electrode systems. As described in the following sections, earpieces were fabricated using 3D printing and electroless gold plating and used to measure drowsiness across multiple users. User data was processed and drowsiness detection was demonstrated with three classifiers (logistic regression, support vector machine, random forest) across three training scenarios. This user study was approved by UC Berkeley's Institutional Review Board (CPHS protocol ID: 2018-09-11395).

II. EXPERIMENTAL OVERVIEW

Twenty-one drowsiness trials were recorded with the Ear EEG system across five healthy users. To enable both user-generic and user-specific training, users participated in multiple trials (maximum of five). Each trial was 40 – 50 minutes

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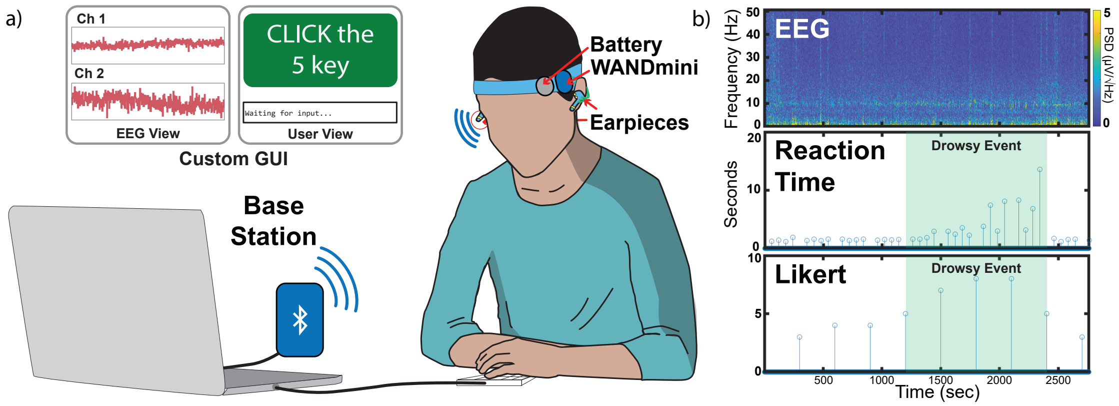

Fig. 2. (a) Experimental setup render. Head-worn WANDmini records and transmits EEG from contralaterally worn earpieces to a base station via BLE. All captured EEG can be live plotted for the trial overseer while a custom GUI records the test user's reaction times and Likert items. (b) Sample spectrogram of single trial's EEG, reaction times, Likert items. Drowsy event shaded in green.

in length and took place indoors between 8am and 5pm with daytime lighting. Prior to each trial, users familiarized themselves with the experiment format and recording set up. Since behavioral and response-time measures are highly correlated to fatigue [2], task-based reaction times and user-reported Likert items were recorded during each trial and used to assign alert and drowsy labels during post-processing.

Users began each trial non-drowsy and seated in front of a laptop. Since the goal of each trial was to record drowsiness onset, users were instructed to play a repetitive game that measured their reaction time to cues on a graphical user interface (GUI). Every 60 seconds, a user was prompted to press a random number between 0-9 (Fig. 2a) and their reaction time was recorded. Every five minutes, the user was prompted to enter a Likert item according to the Karolinska Sleepiness Scale (KSS). This scale ranges from 0 = "extremely alert", to 10 = "extremely sleepy, fighting to stay awake". EEG was recorded with Ear EEG throughout the trial. During initial tests, it became clear that recording from both ears to capture signals across the scalp improved the classifier accuracy by up to 10%. Thus, users wore two user-generic, dry electrode earpieces (one in each ear) and a compact wireless neural recording module WANDmini [5].

After each trial, alert and drowsy labels were assigned based on reaction times and Likert items. Initial drowsy periods were highlighted anytime a user's reaction time exceeded 2.5 seconds. Then to account for momentary distractions (when a user was alert but not looking at the GUI), any period that was not accompanied with a drowsy Likert item was relabeled as alert. Lastly, the starts and ends of drowsy periods were tuned based off the derivatives of a user's reaction times and Likert items. When the derivatives increased, this marked the onset of a drowsy event. When the derivatives decreased, this marked the end of a drowsy event (Fig. 2b). Each trial exhibited at least one drowsy event lasting more than nine minutes. Thirty-six drowsiness events were recorded across all 21 trials.

A. *Ear EEG System Overview*

A user-generic electrode scheme and physical earpiece design capable of recording across multiple individuals is critical for a wearable drowsiness detection platform. Electrode and earpiece designs were derived from [5] to ensure consistent low electrode-skin impedance (ESI) throughout the trial duration. The electrode sizes and locations were selected in order to minimize channel to channel correlation while maximizing electrode area. Earpieces boast four 60 mm^2 canal electrodes and two 4 cm^2 electrodes on the ear's concha cymba and concha cavity (Fig. 3 a,b,c). A contralateral recording arrangement with two earpieces provides up to 10 EEG channels with two candidate reference electrodes. The right concha cymba electrode was used as the reference electrode while the left was ignored.

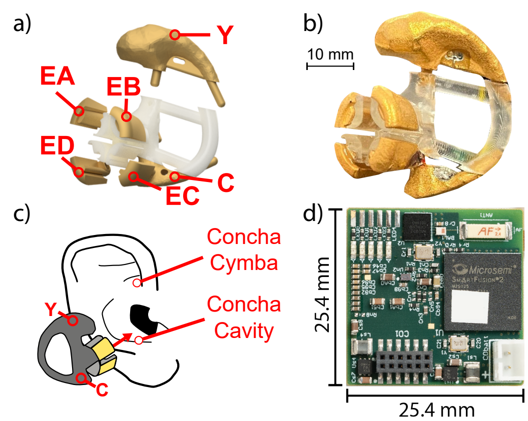

Fig. 3. (a) Earpiece exploded view. (b) User-generic, dry electrode earpiece. (c) Earpiece fit. Y & C contact the concha cymba and cavity, respectively. (d) WANDmini Recording Module.

To maximize comfort during multi-hour sessions and further reduce ESI, the earpieces are modified with a soft skeleton and high-surface area gold plated electrodes. Electrodes were 3D printed with Formlabs tough resin (RS-F2-TO15-01), sand-blasted, and electroless plated with palladium, copper, and gold [9]. This produced a gold-finished electrode that is biocompatible, reusable, and solderable, and thus ideal for integration with existing recording hardware. The earpiece body was 3D printed with Formlabs flexible 80A resin (RS-F2-FL80-01), improving in/on ear flexibility and user comfort. The body exhibited 8.9 MPa of tensile strength and a durometer shore A value of 80, making it more durable and 20% more compliant than [5]. Across five

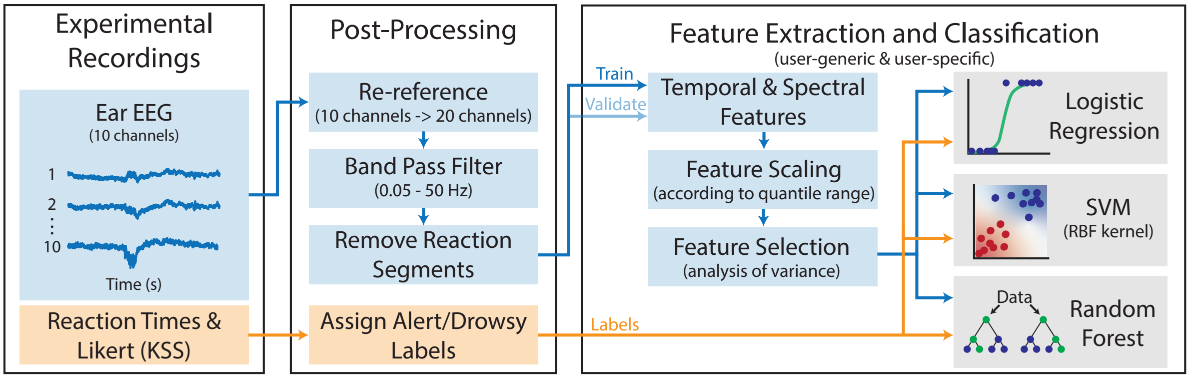

Fig. 4. Block diagram outlining Ear EEG experimental recordings, post-processing, feature extraction and classification to estimate alert and drowsy states. Reaction times and Likert items recorded during the trial are used to assign alert and drowsy labels for classifier training.

users and 30 ESI measurements, in-ear electrodes exhibited an average ESI of 190 kΩ (at 50 Hz) and phase of 29°. Acceptable contact was graded by a 20 Hz ESI $<1M\Omega$; 90% of measurements meet this criterion.

All EEG signals were recorded using a compact neural recording device (WANDmini) (Fig. 3d) that wirelessly transmitted in real-time to a bluetooth base station connected to a laptop. WANDmini's recording, digitization, and serialization are performed by a custom neuromodulation IC [10] (NMIC, Cortera Neurotechnologies, Inc.) that has been extensively used for both intracranial and non-invasive neural recording. The NMIC has stimulation capabilities and 64 digitizing frontends integrated into a compact footprint. This study used 10 channels to record EEG and no stimulation. Relevant electrical specifications are listed in Table I.

B. Drowsiness Feature Extraction and Classification

Post-processing, feature extraction, and classification of the Ear EEG recordings was carried out to detect alert and drowsy states (Fig. 4). To take advantage of contralateral recordings, each in-ear electrode was re-referenced to the left concha cymba electrode to maximize spatial covering. Both originally referenced and re-referenced EEG channels were band pass filtered from 0.05-50Hz in order to target the EEG frequency bands of interest for drowsiness detection. Namely, delta (δ, 0.05-4Hz), theta (θ, 4-8Hz), alpha (α, 8-13Hz), beta (β, 13-30Hz), and gamma (γ, 30-50Hz) [2].

Experimental recordings were divided into 50 second epochs, which began 10 seconds after a reaction time cue and ended when the next reaction time cue was provided. This focused classification on alert and drowsy states by removing EEG artifacts related to decision-making and motor planning in response to GUI cues. If a user's reaction time exceeded 10 seconds, the epoch was considered "sleep" and discarded from this alert and drowsy study. Features were calculated for each 50 second epoch, since maximizing the feature extraction window size maximized classifier accuracy.

Both temporal and spectral features that appear in EEG-based classification literature were implemented [2] [7]. Time-domain features included voltage standard deviation and maximum peak-to-peak voltage amplitude. For frequency characteristics, the power spectral density (PSD) is calculated using Welch's method. Spectral features including maximum PSD, frequency of maximum PSD, and PSD variance were calculated for each EEG band. Absolute and relative band powers were also calculated for the following bands and ratios: δ, θ, α, β, γ, α/β, θ/β, $(\alpha+\theta)/\beta$, and $(\alpha+\theta)/(\alpha+\beta)$. The previous epoch features were used to capture changes between subsequent epochs related to drowsiness onset. To account for outliers and signal artifacts, features were scaled by subtracting the median and scaling according to the interquartile range. During training, analysis of variance feature selection was used to find the 20 features that maximize class variation and minimize redundancy.

Binary (alert/drowsy) classification was performed with three low-complexity classifier models. Logistic regression was implemented with a stochastic average gradient descent solver and L1 regularization, which adds a penalty equal to the absolute value of the magnitude of feature coefficients. A support vector machine (SVM) was implemented with a radial basis function (RBF) kernel that utilizes a maximum of 400 support vectors and a regularization parameter, C=1. A random forest classifier was implemented with 100 trees and a maximum depth of five. Class probabilities returned from these models were filtered with a 3-tap Hamming window FIR filter and thresholded to achieve final binary outputs.

TABLE I

SYSTEM ELECTRICAL SPECIFICATIONS

Maximum Recording Channels	64
Recording Channels Used	10
Input Range	100 mVpp
ADC Resolution	15 bits
ADC Sample Rate	1 kSps
Noise Floor	$70nV/\sqrt{Hz}$
Wireless Data Rate	2 Mbps
Power	46 mW

III. RESULTS

Alert and drowsy event detection performance was estimated with three cross validation techniques of varying practicality: user-specific, leave-one-trial-out, and leave-one-user-out. Commensurate with the state-of-the-art, each classifier's cross validation performance was scored using event-based sensitivity (correctly classified drowsy events), specificity (correctly classified alert events), and accuracy (eq 1).

$$Accuracy = \frac{True\ Drowsy + True\ Alert}{All\ Events} \quad (1)$$

To consider a drowsy event correctly detected, classifiers must detect at least three minutes of consecutive 'drowsy' epochs. This threshold makes classification robust to noisy classifier outputs while ensuring acceptable detection latency. An average detection latency of 3.25 minutes was achieved across all training scenarios. Since this is before the user falls asleep, this latency is acceptable.

User-specific cross validation estimated event detection accuracy with recordings from individual users. The model was trained on n-1 trials for a user and tested on their remaining trial. This process was repeated n times and the results were averaged to estimate overall drowsiness detection accuracy. Average user-specific results ranged from 95.2 - 95.9% across all classifier models (Fig. 5).

Leave-one-trial-out cross validation estimated event detection accuracy with recordings from all users. The model was trained on 20 trials and tested on the remaining trial. This process was repeated 21 times. A 93.9 – 95.4% average event detection accuracy was achieved across models.

Leave-one-user-out cross validation trained the model on recordings from four users and tested on recordings from the never-before-seen user. This user-generic process was repeated five times. Across all classifier models, a 94.5 - 95.0% average event detection accuracy was achieved.

IV. Summary

This work presents dry electrode Ear EEG drowsiness detection. A discreet, contralateral recording system with user-generic earpieces was developed and evaluated with a proof-of-concept drowsiness study (21 trials). Alert and drowsy state detection was demonstrated across three classifier models. When training a SVM classifier with data from all users, a binary-state classification accuracy of 95.4% was achieved. When training a similar SVM model on four users and testing on the never-before-seen user, an accuracy of 94.5% was achieved. To the best of the authors' knowledge, this is the only dry electrode Ear EEG drowsiness detection platform (Table II). Since data is specific to individual users, it is difficult to compare accuracy across platforms. On average, this work performs comparable to or better than state-of-the-art scalp and in-ear EEG drowsiness detection systems.

TABLE II
Table Comparing Recent In-ear/scalp Drowsiness Detection

	[8]	[6]	[7]	[2]	This work
# Users	13	23	16	30	5
# Recordings	13	184	16	312	21
Recording length (min)	60-90	20	55-75	30	40-50
In-ear/Scalp	In-ear	In-ear	In-ear	Scalp	In-ear
single/both ears	Single	Single	Single	–	Both
Wet/Dry	wet	wet	wet	wet	dry
# channels	1	2	1	30	10
Epoch size (s)	5s	30s	230s	60s	50s
Models	SVM	SVM	RF	SVM	SVM
Sensitivity	–	91.2%	99.0%	94%	95.0%
Specificity	–	–	96.0%	92%	96.7%
Accuracy	88.3%	82.9%	98.5%*	93%	95.9%

*For 230s epoch. 95% accuracy achieved for 60s epoch

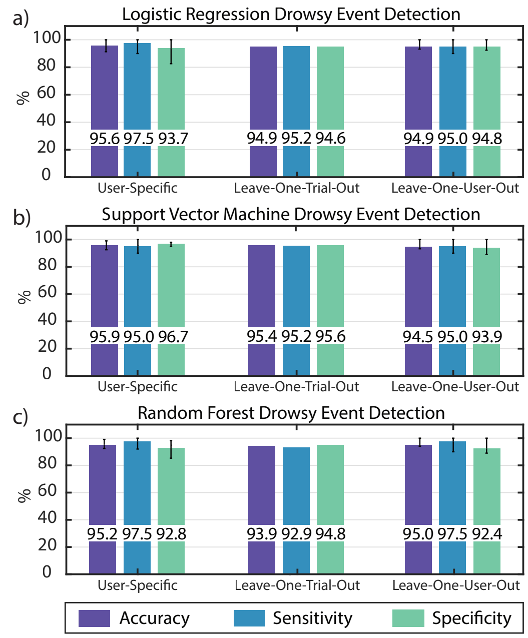

Fig. 5. Drowsy-event detection across three classifier models a) logistic regression, b) support vector machine, c) random forest. For each model, results are shown for user-specific, leave-one-trial-out, and leave-one-user-out cross validation. Error bars show minimum and maximum user results.

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