Automatic detection of drowsiness using in-ear EEG

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***Abstract*—Sleep monitoring with wearable electroencephalography (EEG) has recently been validated and reported in the research community. One such device is our ultra-wearable, unobtrusive, and inconspicuous in-ear EEG system, which has already been demonstrated to be next-generation solution for out-of-clinic sleep monitoring. We here provide a further proof of concept of the utility of ear-EEG in day time drowsiness monitoring in the real-world. For rigour, hypnograms are obtained from manually scored daytime nap recordings from twenty-three subjects, while a complexity science feature – structural complexity extracted from scalp- and ear-EEG recordings – is used in the classification stage, in conjunction with a binary-class support vector machine (SVM). The achieved drowsiness classification accuracies range from 80.0 % to 82.9 % for ear-EEG, with the corresponding accuracies for scalp-EEG ranging from 86.8 % to 88.8 %. Given the notoriously difficult to classify drowsiness related changes in EEG (similar to the issues with the NREM Stage 1), this conclusively confirms the feasibility of in-ear EEG for automatic light sleep classification. This also promises a key stepping stone towards continuous, discreet, and user-friendly wearable out-of-clinic drowsiness monitoring in the real-world, with numerous applications in the monitoring the state of body and mind of pilots, train drivers, and tele-operators.**

I. Introduction

Although the function of sleep is not yet fully understood, sleep is strongly linked to quality of life. For example, the lack of sleep during the night contributes to the feeling of tiredness, and poor memory and work performance. The concept of 'sleepiness' can be interpreted as a tendency towards sleep; the inability to concentrate or to keep eyes open may indicate a higher level of sleepiness. For several decades, multiple researchers have investigated sleepiness and performance capacities related to physiological patterns, especially electroencephalography (EEG) and electrooculography (EOG) for shift workers [1, 2], and for healthy subjects [3, 4]. These studies have shown that the alpha and theta activity, in particular, exhibit significant correlations between both subjective and objective measures of sleepiness. Physiological patterns have been investigated and linked to mental workload using a driving simulator for healthy subjects [5, 6], while a recent study of obstructive sleep apnea (OSA) patients elucidated that auditory event related potentials, appear to be a significant parameter to predict poor driving performance [7].

In order to uncover physiological characteristics of certain states of body and mind, such as sleepiness, a multitude of physiological electrodes are required. In terms of sleep monitoring, polysomnography (PSG) recordings have been traditionally used in clinic to diagnose various sleep disorders. Typically, PSG recordings require at least two EEG channels, two electrooculography (EOG) channels to observe eye movements, and at least one chin electromyography (EMG) channel. However, this conventional setup is both a cumbersome and expensive procedure as it requires a trained clinician; this is therefore prohibitive to the physiological states in the real-world.

Automatic sleep staging systems have been proposed based on PSG recordings; this was originally motivated to replace the time-consuming sleep stage scoring process by clinicians. The state-of-the-art approaches include single-channel scalp-EEG based classification, and are validated using various benchmark datasets [8, 9]. For wearable sensing, ear-EEG technology [10] has been recently proposed in sleep monitoring, using an in-ear system [11, 12], and an around-ear system [13]; these can vastly improve the technically cumbersome setup. Our latest in-ear EEG sensor is readily wearable by users, and does not disturb their daily activities. The quality of the signal from in-ear sensors has been extensively investigated in different scenarios, such as comparing steady-state responses to conventional scalp-EEG [10] and cardiac activity [14]. As well as scalp-EEG based sleep monitoring systems, the in-ear EEG has been recently used for automatic sleep staging by machine learning algorithms [15, 16]. Hence, the unobtrusive and wearable in-ear sensors have been validated in sleep monitoring applications and are capable of monitoring physiological responses out-of-clinic. We here further investigate the in-ear sensing capability in the area of day time sleepiness.

Sleepiness is a symptom and a subjective parameter, which depends on how an individual perceives the degree of urge to fall a sleep. The exact cause of sleepiness is still under investigation, but one cause could be a lack of sleep during the night. The state of being sleepy appears to be linked to 'drowsiness', which is the transition from wakefulness to light sleep. For the 'drowsiness' classification, Patrick *et al.* conducted automatic sleep staging using a publicly available dataset [17], and only extracted wake and Non-REM Stage 1 [18]. Their selected features from a single EEG channel and computationally inexpensive classification algorithm can detect sleep onset effectively, and in the real-world scenarios.

We previously conducted daytime nap recordings with

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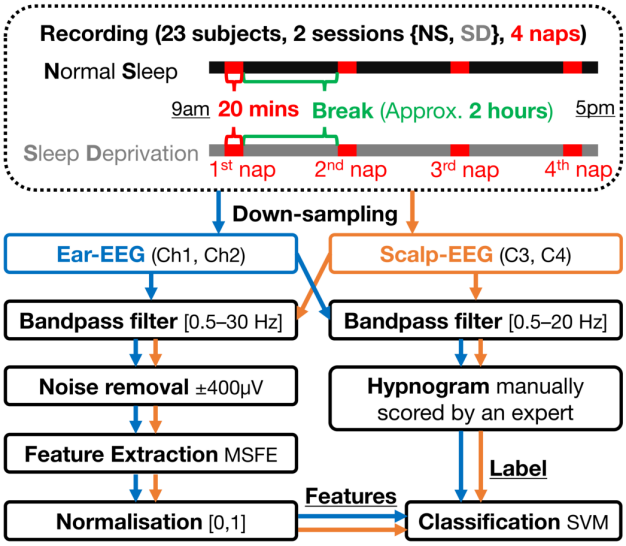

Fig. 1. Flowchart for the classification framework in this study.

TABLE I
THE CONFIGURATION OF EEG RECORDINGS

No. of subjects	23
No. of sessions	2 days (Normal sleep, Sleep deprivation)
No. of trials per session	4 trials
Length of trial	20 mintutes
Channels	Scalp-EEG (C3, C4) Ear-EEG (Ch1, Ch2)

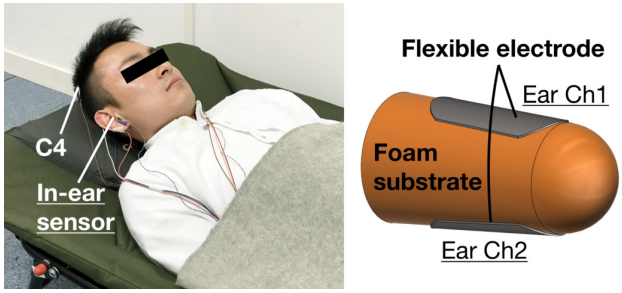

Fig. 2. Left: Recording setup. The electrodes were placed on scalp and in the ear canal. The subject seated and reclined in a comfortable chair. Right: The wearable viscoelastic in-ear sensor with two flexible electrodes [22].

conventional scalp-EEG headsets and our in-ear EEG sensor simultaneously, and found substantial agreement between the two, which indicates the feasibility of in-ear EEG for measuring sleep latency [19] in healthy volunteers [20]. In this paper, we use the same day time nap EEG data, and validate whether in-ear EEG patterns can distinguish between wakefulness and light sleep. The results provide a conclusive evidence that, due to the unobtrusive and wearable nature of our in-ear sensor, the light sleep classification application with in-ear sensing is capable of achieving 'drowsiness' monitoring in the real-world.

II. Methods

Figure 1 summarises the analysis framework for this study. The recorded scalp- and ear-EEG data were manually scored by a clinician. The data were also pre-processed and supervised classification was performed.

A. Data acquisition

The EEG data were recorded at Imperial College London between December 2015 and April 2016 under the ethics approval, ICREC 12_1_1, Joint Research Office at Imperial College London. Twenty three healthy subjects (28.5±5.3 years) participated in the recordings. Subjects were instructed to participate in two recording sessions; each session was executed between 9 am to approximately 5 pm. The subjects attended the recordings after either their normal sleep (average $\geq$ 7 hours) or sleep deprivation ($\leq$ 5 hours) in the night before, and refrained from consuming caffeine. The subjects performed four naps (trial) with the length of 20 minutes on each recording day, and the interval between trials were approximately 2 hours. If needed, participants were allowed to leave the lab in between naps (e.g. for toilet break or bringing in the lunch). The sensors were kept in place throughout the trials, unless requested by participants, or to reapply the electrodes due to poor electrode impedance. Overall, 21 out of 23 subjects participated in both recording sessions. Table I summarises the recording details.

Scalp- and ear-EEG were recorded simultaneously using the g.tec g.USBamp amplifier with 24-bit resolution, at a sampling frequency fs = 1200 Hz. For scalp-EEG, standard gold-cup electrodes located at the C3 and C4 position (according to the international 10-20 system) were used for the recordings, a montage extensively used in sleep medicine for visual sleep scoring, and the ground electrode for scalp-EEG recordings was attached to the forehead.

The in-ear sensor was made based on a 'one-fits-all' viscoelastic earplug with two flexible electrodes, the details can be found in [21, 22]. The size of in-ear sensors was the same for all subjects. The in-ear sensor was inserted into either subject's left or right of ear, according to their preference. After the insertion, the sensor expanded to conform firmly to the shape of the ear canal. The standard gold-cup electrodes were attached behind the ipsilateral helix and the ipsilateral earlobe for reference and ground, respectively. After the electrodes were attached, the subjects were instructed to seat and recline in a comfortable chair in a dark and quiet room. Figure 2 illustrates the recording setup (left) and our in-ear sensor based on 'generic earpiece' (right).

B. Manual scoring

The recorded signal was first downsampled to 200 Hz, and a fourth-order Butterworth bandpass filter with passband 1 – 20 Hz was applied to both scalp- and ear-EEG. The processed scalp- and ear-EEG data were blinded and separately scored based on the American Academy of Sleep Medicine

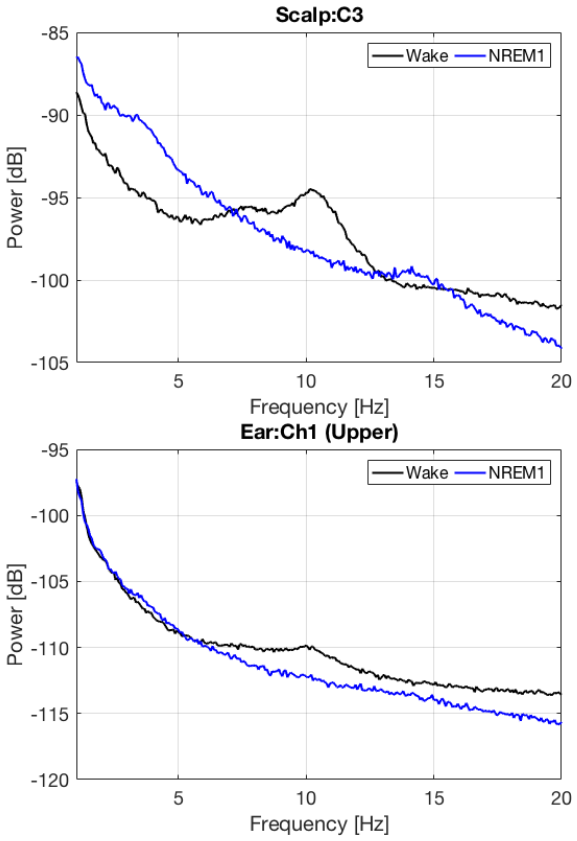

Fig. 3. Averaged power spectral density for the scalp C3 channel (top) and in-ear EEG Ch1 (bottom).

(AASM) criteria [23]. The epoch size was set to 30 s, therefore 40 epochs were scored in each recording trial (30 s×40 epochs = 1200 s). Some recording trials were too noisy to score; one typical issue was when a subject put the side of their head on the pillow, the earpiece and cables could become trapped underneath of their heads. Overall, 161 trials were used for further analyses. Note that some subjects did not sleep at all during the 20 minutes trials, so in this scenario, the hypnograms from such trials were all scored as Wake.

TABLE II
PROPORTION OF SLEEP STAGES OVER 23 SUBJECTS

Dataset		Wake	NREM1	Total
Ear-EEG	No. of epochs	3997	2002	5999
	Ratio (%)	*66.6*	*33.4*	*100.0*
Scalp-EEG	No. of epochs	3728	2071	5799
	Ratio (%)	*64.3*	*35.7*	*100.0*

C. Pre-processing

For classification analyses, the downsampled EEG signals were bandpassed with a fourth-order Butterworth filter with passband from $0.5 - 30$ Hz. Since this study focus on a detection of drowsiness, which is the boundary between wakefulness and Non-REM Stage 1 (NREM1), we only analysed the epochs labeled as Wake and NREM1. In order to remove noisy epochs from further analyses, for each scalp- and ear-EEG, the epochs (i.e. 30 s segment of recordings) which contained amplitudes of more than $\pm 400\,\mu$V were removed. Therefore, the total number of scalp- and ear-EEG epochs for further analyses was different, with their proportion given in Table II.

Figure 3 illustrates the averaged power spectral density (PSD) over 23 subjects for scalp-EEG channel (C3) and in-ear EEG channel (Ch1, upper electrode), corresponding to Wake and NREM1 conditions. Even though the amplitude of scalp-EEG was different to that of ear-EEG, the trends of PSD were similar. For example, for both scalp- and ear-EEG channels, there is a close match between the peaks in the alpha band $(8 - 13$ Hz) for Wake, and the alpha power attenuation in the NREM1.

D. Feature extraction

After the pre-processing, the multi-scale entropy (MSE) metrics [24–26] were calculated for each epoch of both scalp- and ear-EEG data. In particular, the multi-scale fuzzy entropy (MSFE) [27] were used for our previous automatic sleep staging work [9] using publicly available overnight Sleep-EDF [expanded] dataset [28].

The MSE is a non-parametric method for estimating dynamical complexity over multiple scales of a time series. The fuzzy entropy (FE) algorithm [29] was used in this study as it is robust to noise and relatively consistent, independent of data length; this consistency makes it well suited to relatively short physiological signals, which in turn makes it appropriate for use with small embedding dimensions.

The maximum scale for the MSFE was $\tau = 30$. Since there are two channels of EEGs for both scalp- and ear-EEG, $30 \times 2 = 60$ features were extracted from each epoch for the classification. Figure 4 depicts MSFE analysis for scalp- and ear-EEG channels (C3 and in-ear Ch1) of the 161 trials over 23 subjects with different sleep stages. Observe that for both scalp- and ear-EEG, the Wake and NREM1 were visually well separated. The parameters used to calculate the MSFE were the same as in our previous work, and can be found in [9].

E. Classification

The binary-class support vector machine (SVM) was employed as a classifier [30]. The radial basis function (RBF) kernel was used for the SVM, which given by

$$\kappa(\mathbf{x}, \mathbf{x}') = \exp(-\gamma|\mathbf{x} - \mathbf{x}'|^2). \quad (1)$$

The regularisation parameter was set to $C = 10$, and the hyper-parameters for classification were set to $\gamma = 1$; the same hyper-parameters were used throughout the analysis.

III. RESULTS

A. Evaluation

The pre-processing and feature extraction analyses were undertaken using Matlab 2016b, and the classification was

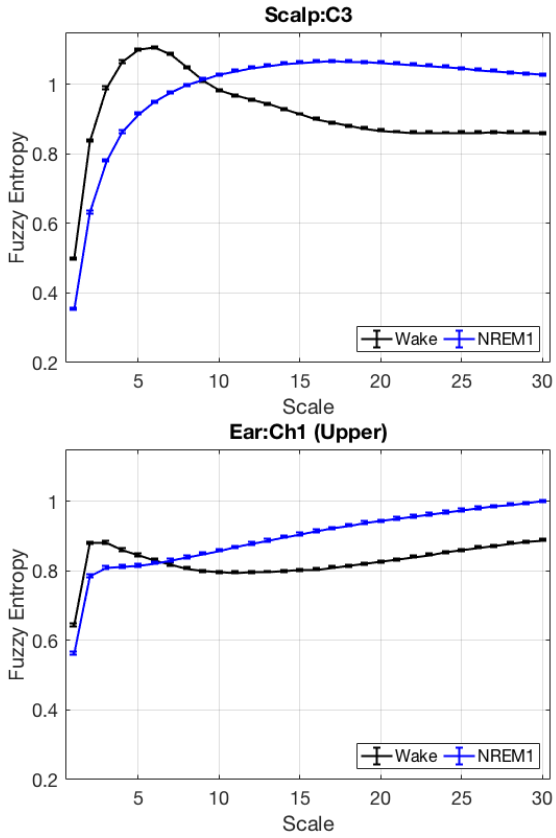

Fig. 4. The averaged multi-scale fuzzy entropy for scalp- and ear-EEG. The error bars represent the standard error.

implemented in Python 2.7.12, Anaconda 4.2.0 (x86_64) operated on an iMac with 2.8GHz Intel Core i5, 16GB of RAM. The class-specific performance metrics used were the sensitivity ($SE = TP/(TP + FN)$) and precision ($PR = TP/(TP + FP)$), where TP (true positive) represents the number of positive (target) epochs correctly predicted, FN (false negative) represents the number of positive epochs incorrectly predicted as negative class, and FP (false positive) is the number of negative epochs incorrectly predicted as positive class. The overall performance was evaluated by the accuracy (AC) and Kappa coefficient (κ) metrics [31], defined as:

$$AC = \frac{\sum_{i=1}^{M=2} TP_i}{N_{epoch}}, \quad \kappa = \frac{AC - \pi_e}{1 - \pi_e},$$
$$where \ \pi_e = \frac{\sum_{i=1}^{M=2} \{(TP_i + FP_i)(TP_i + FN_i)\}}{{N_{epoch}}^2}.$$

The parameter $M = 2$ is the number of classes (i.e. Wake or NREM1), and N_{epoch} is the total number of epochs.

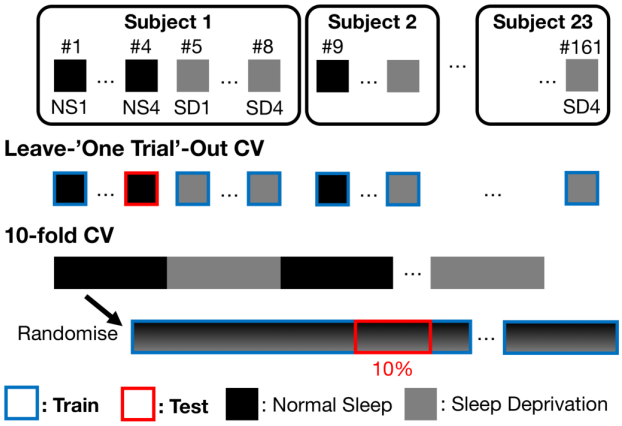

Fig. 5. Cross validation approaches used in this study.

B. Validation setup

Figure 5 illustrates the two different validation methods employed in this study. First, we applied the Leave-'One Trial'-Out Cross-Validation (LOTOCV) approach; a single nap trial was assigned as test data and the rest of 160 trials was used as training data (as mentioned in Section II-B, the number of epochs was 161). The validation trials were therefore repeated 161 times. Although this approach is computationally expensive, the test and training data do not come from the same recording trial, therefore, this approach is applicable for real world setups. Second, a 10-fold CV approach was utilised, whereby EEG recordings from all the 161 trials with scored hypnogram were concatenated into one large matrix, and then randomly split into the training data (90 %) and test data (10 %).

C. Setup1: LOTOCV

Tables III and IV show the classification results using Leave-'One Trial'-Out CV (LOTOCV) methods for ear-EEG and scalp-EEG recordings, respectively. For ear-EEG, the classification accuracy of two stages (i.e. Wake or NREM1) was 80.0 % with the kappa coefficient of κ = 0.53. The classification and corresponding kappa for scalp-EEG were 86.8 % and κ = 0.72 (substantial agreement), respectively.

TABLE III
CONFUSION MATRIX FOR THE 2-CLASS WAKE VS. NREM1 CLASSIFICATION (EAR-EEG, LEAVE-'ONE TRIAL'-OUT CV)

		Algorithm based on ear-EEG		
		Wake	NREM1	SE(%) / PR(%)
Hypnogram based on ear-EEG	Wake	3546	451	88.7 / 82.5
	NREM1	750	1252	62.5 / 73.5
Accuracy: 80.0 %, Kappa = 0.53				

D. Setup2: 10-fold CV

Tables V and VI show the confusion matrices for 10-fold CV methods using ear-EEG and scalp-EEG, respectively.

TABLE IV
CONFUSION MATRIX FOR THE 2-CLASS WAKE VS. NREM1 CLASSIFICATION (SCALP-EEG, LEAVE-'ONE TRIAL'-OUT CV)

		Algorithm based on scalp-EEG		
		Wake	NREM1	SE(%) / PR(%)
Hypnogram based on scalp-EEG	Wake	3316	412	88.9 / 90.4
	NREM1	353	1718	83.0 / 80.7
Accuracy: 86.8 %, Kappa = 0.72				

The classification accuracy for ear-EEG was 82.9 % and the corresponding kappa was $\kappa = 0.60$. For scalp-EEG, the classification accuracy and kappa were 88.8 % and $\kappa = 0.76$ (substantial agreement), respectively.

TABLE V
CONFUSION MATRIX FOR THE 2-CLASS WAKE VS. NREM1 CLASSIFICATION (EAR-EEG, 10-FOLD CV)

		Algorithm based on ear-EEG		
		Wake	NREM1	SE(%) / PR(%)
Hypnogram based on ear-EEG	Wake	3645	352	91.2 / 84.4
	NREM1	673	1329	66.4 / 79.1
Accuracy: 82.9 %, Kappa = 0.60				

TABLE VI
CONFUSION MATRIX FOR THE 2-CLASS WAKE VS. NREM1 CLASSIFICATION (SCALP-EEG, 10-FOLD CV)

		Algorithm based on scalp-EEG		
		Wake	NREM1	SE(%) / PR(%)
Hypnogram based on scalp-EEG	Wake	3374	354	90.5 / 92.0
	NREM1	295	1776	85.8 / 83.4
Accuracy: 88.8 %, Kappa = 0.76				

IV. DISCUSSION AND CONCLUSION

This study aims to classify 'drowsiness', which is an important condition on the boundary between wakefulness and light sleep. We conducted day time nap recordings from twenty three healthy subjects, and automatically classified their sleep stages based on EEG signals obtained from both on-scalp and in-ear sensors. Our previous study scored and compared the sleep onset based on both scalp- and ear-EEG [20], where the results achieved in this study have confirmed the feasibility of in-ear EEG for automatic light sleep classification, which is applicable for wearable out-of-clinic drowsiness monitoring.

The classification accuracies of scalp-EEG were better than those of ear-EEG in both LOTOCV and 10-fold CV approaches. The feature used for classification was the MSFE, see Figure 4. The separation of ear-EEG in different sleep stages has not been visually significant compared to that of scalp-EEG, therefore the classification based on scalp-EEG was slightly better than that by ear-EEG. Regarding the classification algorithm, the same regularisation parameter C, the type of kernel, and hyper-parameter γ were used in both LOTOCV and 10-fold CV for both scalp- and ear-EEG, therefore further parameter tuning can improve the classification performance.

In this pilot study, we have only used one earpiece to monitor in-ear EEG, which is wearable and readily collectable system. Recently, we have proposed in-ear electrocardiogram (ECG) monitoring [32] using two earpieces, which can be incorporated into a for further study, giving a different in-ear physiological measurement, which enhances the feasibility of out-of-clinic drowsiness monitoring.

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