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Sensor system application

Configurable mobile system for autonomous high-quality sleep monitoring and closed-loop acoustic stimulation

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Abstract— Present-day sleep research in humans is largely dependent on complex and costly laboratory setups that require controlled supervision. As it is highly desirable to study sleep and monitor sleep interventions in a realistic setting at home, new mobile approaches with equivalent performance to lab-based systems are needed. We present here the development and evaluation of a mobile system for sleep biosignal monitoring and real-time intervention for ambulatory sleep research. We evaluated the system for electroencephalogram (EEG) signal quality and compared it to an established sleep EEG recording system. The real-time EEG signal processing performance was evaluated by implementing a closed-loop auditory deep sleep stimulation algorithm and calculated the precision of slow wave (SW) phase targeting during 93 nights. The obtained EEG signals contained similar power spectrograms and high correlations in the delta (0.98) and sigma (0.99) bands when compared to the reference system. The SW phase targeting (mean 44.6°, standard deviation 46.8°) was comparable to previously published, lab-based approaches. We have thus demonstrated that our device is suitable for performing unobtrusive, multi-night monitoring and intervention at home.

Index Terms— Sensor systems application, biosignal sensing and processing, sleep, mobile devices, EEG.

I. INTRODUCTION

Human sleep research typically relies on high-end electroencephalogram (EEG) systems, conducted and controlled by trained personnel in laboratory environments. As lab-based approaches require complex and costly set-ups, sleep studies have been restricted to a low number of participants and a very few nap or night sessions, limiting their translation to generalizable, real-world findings. In addition, the low number of samples limits the identification of inter-individual differences.

Ambulatory sleep research with ubiquitous monitoring systems could overcome these limitations. Subjects could be monitored over much longer durations in a realistic environment at reduced cost. However, the remote use of existing sleep monitoring technology is not trivial, since the size and usability is not adapted to the needs and competences of the lay users. Recent efforts in system miniaturization made unobtrusive, mobile EEG available, such as smartphone connected EEG for drowsiness detection [1] and around-ear EEG for sleep staging [2]. Large focus has been put to enhance comfort on electrode application with printed electrodes [3], or automated sleep classification using machine learning methods [4], [5]. Furthermore, consumer devices that detect and stimulate slow wave sleep (SWS) have also been developed [6], [7]. However, these consumer solutions have very limited research applications, as they use proprietary and nontransparent data processing and management, as well as do not offer flexibility with EEG channel selection and system configuration.

To overcome this existing gap, we have designed the Mobile Health Systems Lab Sleep Band (MHSL-SB), a configurable mobile system for EEG and sleep research at home. For the first time, we present an entirely portable device for biosignal monitoring and real-time processing that provides data and processing transparency, as well as flexible electrodes positioning, to specifically enable advanced sleep research and clinical applications such as embedded closed-loop acoustic stimulation. The aim of this work was to (1) evaluate if the device specifications and sensor signal quality are suitable for sleep research, (2) benchmark the real-time EEG signal processing capabilities, and (3) test the device usability and data integrity during user self-application over multiple nights at home. We provide an overview of the developed system and the implemented algorithms, and demonstrate that the MHSL-SB is an alternative to lab-based equipment for state-of-the-art ambulatory sleep research.

II. SYSTEM DESCRIPTION

The MHSL-SB is a portable, battery powered 8-channel biosignal monitoring and processing device. We designed the MHSL-SB to be comfortable and easy to apply, while providing a modular and configurable research platform (Fig. 1). The system featured a custom headband to attach electrodes, cables, and headphones, enabling electrode placement at all head locations. In our specific configuration, we implemented an electrode configuration that is frequently used for sleep stage classification: EEG, electrooculography (EOG) and electromyography (EMG, Fig. 1(a)). A portable casing provided access to the SD card, USB charging, 3.5 mm audio jack, and the analog biosignal connector, which also served as a power switch (Fig. 1(d)). As a safety feature, a mechanical slider prevented simultaneous access to the charging and analog connectors.

A. System architecture

The MSHL-SB electronics were designed to provide high performance signal acquisition and processing, and were conceptually divided into four units (Fig. 1 (b)):

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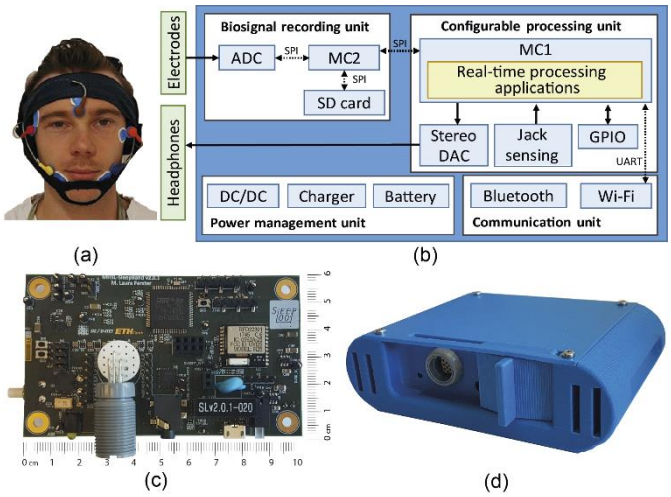

Fig. 1. The MHSL-SB (a) headband, (b) system architecture, (c) printed circuit board, and (d) portable casing. When the headband cable was plugged into the analog connector, the system autonomously started biosignal recording and processing without additional user input.

Configurable processing: An ultra-low-power ARM Cortex-M4 based microcontroller (MC1) provided real-time digital signal processing. A stereo digital-to-analog converter to play sounds at minimal delay was added and complemented with a sensing circuit to detect if headphones were correctly connected to the device. In addition, general purpose input/output (GPIO) connectors were added to enable additional peripherals and communication channels.

Biosignal recording: A high-end 8-channel 24-bit analog-to-digital converter (ADC, ADS1299, Texas Instruments Inc, USA), selected for its low noise and programmable gain, was combined with a 32-bit low-power microcontroller (MC2). The MC2 recorded the biosignals at 250 Hz to the SD card and coordinated the communication between the ADC and configurable processing unit.

Power management: A medical grade DC/DC converter protected the device from electrical hazards. A 5 V charging and overload protection circuit managed a CE marked 2600 mAh Li-Ion battery that provided power autonomy of up to 24.5 hours.

Communication: Wi-Fi and Bluetooth modules for wireless data transmission and system configuration were added.

B. Biosignal processing

To validate the onboard signal processing capability of our system, we implemented real-time EEG processing and classification algorithms coupled with auditory feedback. It has been shown that tones played in phase with slow waves (SW) during non-rapid eye movement (NREM) sleep boost slow wave activity (SWA) [8]. To achieve this effect, a system must sense, process and classify the EEG, as well as trigger the auditory stimuli within a few milliseconds during a positive phase of the SW. A trigger in the negative phase would lead to a negative effect with reduced SWA [8], [9]. Therefore, the closed-loop stimulation of SW is an excellent showcase to demonstrate efficient and precise real-time biosignal processing.

The implemented closed-loop stimulation algorithm was based on a cascade of sub-algorithms that processed a single EEG signal (Fpz-M2) which was preprocessed with a 50 Hz notch filter to eliminate power line noise.

Sleep classification. This binary classifier categorized the EEG data as NREM sleep (sleep stages N2 and N3 characterized by SW and sleep spindles) or not-NREM sleep (awake, N1, and REM) based on the delta and high beta spectral power, and their ratio calculated from the past 80 s of EEG. If the powers or ratio crossed predefined thresholds, the EEG signal was classified as NREM sleep and the SWA classification, beta power detection, and EEG phase estimation algorithms were executed.

SWA classification. SWA was detected when the delta power calculated over the last 4 s of the filtered EEG (Butterworth second order) exceeded a power threshold.

EEG phase estimation. We introduced a first-order phase-locked loop (PLL) architecture to estimate the phase of the input EEG signal previously filtered with a 0.1 Hz high pass filter to remove the DC offset. The proposed PLL was a linear combination of a multiplier and a numerical controlled oscillator (NCO) [10]. The NCO frequency was set at 1 Hz to follow the frequency variations in the SW range (0.5 – 4 Hz). When the estimated phase reached a 45° phase, the EEG phase condition was satisfied. The PLL parameter, which is the combination between the two components' gain, was selected to maximize the stimulation triggers during the SW ascending positive phases (from 0° to 90°) and increase the phase accuracy around 45°.

Beta power detection. Power increments in the beta frequency range has been related to awake, light sleep, artifacts, and the presence of arousals [11]. Thus, this algorithm prevented stimulations when high beta power was detected in the EEG of the past second.

Stimulation decision logic. The acoustic stimuli were triggered when the SWA, EEG target phase, beta power, and minimal NREM sleep duration of 3 min conditions were simultaneously met.

The above algorithms have configurable thresholds to adjust the system to various sleep patterns observed in different individuals and populations. We aimed to have high trigger accuracy during NREM sleep and SW ascending positive phase for which thresholds were determined using sleep data from 11 healthy subjects (unpublished).

III. SYSTEM PERFORMANCE ANALYSIS

A. Signal quality

To investigate if the MHSL-SB signal quality was suitable for sleep research, we compared the signals to a state-of-the-art recording system. An overnight (9 h) recording of a young female volunteer (31 years old) with the MHSL-SB and a CE certified reference device (Embla Titanium [12], Embla Systems LLC, USA) was performed. Two channels (Fpz and M2) were simultaneously recorded using a 2-channel signal splitter and two independent ground connections. We synchronized the signals and resampled the reference EEG (256 Hz) to the MHSL-SB sampling frequency (250 Hz).

To compare the power distribution of each signal over the entire night, we calculated the power over the 0.5 – 25 Hz frequency range in epochs of 20 s using the pwelch function (Hanning window, average of five 4–s windows). Additionally, we computed the delta (0.5 – 4 Hz) and sigma (10 – 15 Hz) mean square power in epochs of 5 min during classified NREM sleep and assessed the correlation between both recordings. Additionally, we presented both signals to

a sleep expert to visually determine whether typical sleep patterns (e.g. spindles and SW) could be distinguished.

B. Performance assessment

After informed written consent, 7 healthy participants (age 63 to 69 years, 5 males) without diagnosed sleep or neurological disorders were included. These participants were part of a larger ongoing clinical trial (NCT03420677), where they used the system independently at home and without any external supervision. For the purpose of this work, we used data from 14 consecutive nights per participant, where no tones were played, but the device computed the triggers in real-time and recorded them for analysis. The clinical trial protocol was approved by the local ethics committee and the Swiss Agency for Therapeutic Products Swissmedic.

Biosignals were recorded with auto-adhesive electrodes (Neuroline 720, Ambu A/S, DK) placed at seven positions: EEG (Fpz), reference (M2), and ground (M1), as well as two EOG and two EMG channels (Fig. 1(a)). A sleep expert visually scored sleep of two random nights per participant in accordance with AASM criteria [11] using 20 s epochs, resulting in a subset of 14 scored nights across all participants.

We assessed the success rate to deliver the tones during NREM sleep by comparing the simulated stimulation triggers with the expert sleep scoring of NREM and not-NREM sleep. The ratio between the number of triggers that took place during NREM sleep and the total number of triggers was calculated over all 14 scored nights. This ratio was indicative of how well the sleep classification and high beta detection algorithms performed in real-time.

Furthermore, we analyzed the precision of targeting the SW ascending positive phase. To serve as ground-truth, the EEG phase was extracted from the preprocessed EEG signal by using a zero-phase FIR filter over the 0.5 – 4 Hz frequency band and then applying the Hilbert transform. We determined the Hilbert phase at the recorded trigger times and calculated the median and interquartile range (IQR) and, to compare with other published work, the mean and standard deviation (SD). We depicted the trigger phase distribution in a histogram. All analysis was performed using MatLab 2017b (Mathworks Inc, USA).

IV. RESULTS AND DISCUSSION

Signal quality. The power showed a very similar distribution across frequencies between the MHSL-SB and the reference device (Fig. 2). The power across time had a correlation of 0.98 for the delta and 0.99 for the sigma frequency bands during NREM sleep and close visual overlap with slightly different amplitude (Fig. 3). Typical NREM sleep patterns, such as spindles and SW, were clearly identifiable in both recordings (Fig. 4). Thus, the spectral and temporal features showed that the signals acquired by both devices were comparable and the MHSL-SB could be an effective alternative to existing systems used in sleep research.

Performance assessment. From 98 nights recorded, 5 were excluded from the analysis: 2 nights due to SD card data corruption, 2 incomplete nights due to partially charged batteries, and only 1 night had poor EEG data quality.

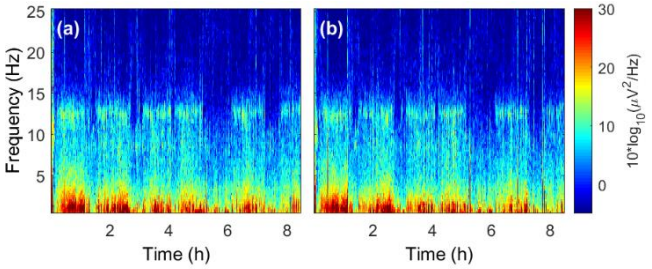

Fig. 2. EEG spectrograms of a sleep night recording were highly comparable between the (a) reference device and (b) MHSL-SB.

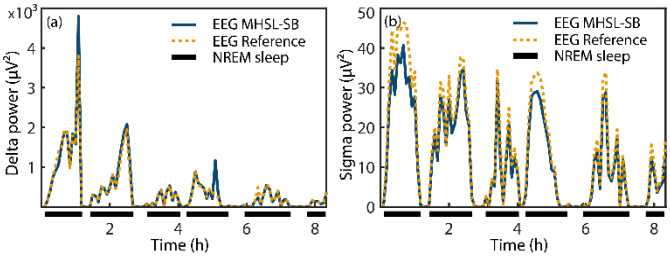

Fig. 3. Mean square signal power in the (a) delta and (b) sigma frequency bands during detected NREM sleep episodes (black blocks) showed high correlation between the MHSL-SB and reference device.

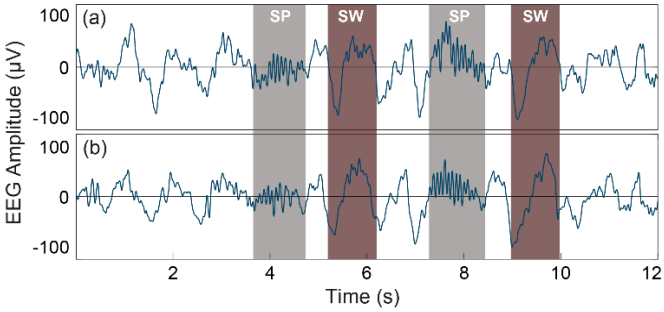

Fig. 4. Typical NREM sleep patterns such as spindles (SP) and slow waves (SW) are clearly apparent in the EEG during NREM sleep in the (a) reference and (b) MHSL-SB device.

The low rate of data loss due to user error (1%), combined with reports from all users that the device was not tedious to use and did not hinder falling asleep, suggested that the device was easy to use in a home setting. While lab-based sleep studies invest considerable time and resources in the set-up and supervision of the interventions, our system design and automated approach minimized this supervision effort, without compromising data quality.

Across all 93 nights, a total of 360'571 triggers were recorded, where 75.7% of them occurred in the 0° to 90°, 14.2% in the 90° to 180°, 3% in the -180° to -90°, and 7.1% in the -90° to 0° phase (Fig. 5). Our algorithm reached a phase distribution with a median of 41.7°, IQR of [21.2°, 68.8°], and a mean of 44.6° (SD 46.8°). These were comparable to other lab-based results reported in healthy young [13], [14] and older adults [15] (Table 1). Therefore, the algorithms presented here minimized undesired stimulation triggers in the SW negative phase that are known to lead to SWA reduction [9]. Since SWA is reduced with increasing age [16], the older participants investigated in this study presented a higher challenge for real-time SW phase targeting, which was adequately addressed with the MHSL-SB.

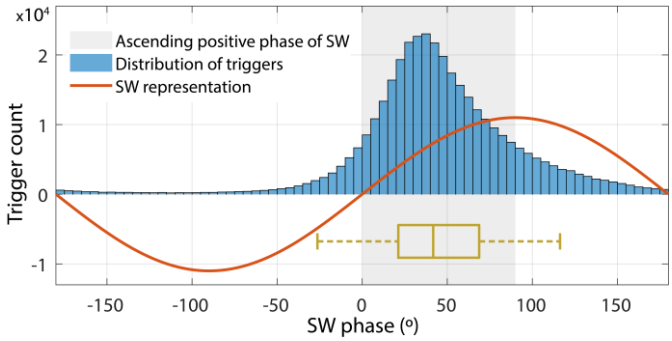

Fig. 5. The triggers are distributed around the ascending positive phase (shaded) of SW (n = 93 recordings). The boxplot (without outliers) illustrates the statistical phase distribution of the triggers. During negative phase the number of triggers is minimized.

Table 1. Stimulation trigger phase's mean and standard deviation (SD) of the proposed system in comparison with reported results of existing lab-based SWS acoustic stimulation approaches.

Phase (°)	Ong et al. [13]	Santostasi et al. [14]	Papalambros et al. [15]	MHSL-SB
mean	52.3	60	59.7	44.6
SD	50.3	25.6	73.1	46.8

In the 14 nights with sleep scoring available, 55'065 triggers were recorded, of which 53'687 (97.5%) occurred in NREM sleep and 1.09% in N1, 1.08% in REM, and 0.33% in Wake. Compared to a recent lab-based study with a comparable elderly population which reported 86.9% of stimulations during NREM sleep (N1 9%, REM 1.7%, Wake 2.4%) [15], our system achieved a high percentage of triggers during the desired NREM sleep.

V. CONCLUSION AND FUTURE WORK

Advanced sleep research involving EEG, which includes the exploration of closed-loop acoustic sleep stimulation intervention, has been restricted to costly and complex laboratory conditions, limiting the number of participants and preventing the generalization of the findings to real-world applications. To overcome these limitations, we have introduced a configurable mobile device for sleep biosignal monitoring and real-time processing and configured it for closed-loop stimulation of SW.

Results showed that stimulation are triggered with an accuracy level equivalent to lab-based systems. From a user's perspective, the MHSL-SB is portable, unobtrusive, and easy to apply. For researchers, the device provides freedom in system configuration and access to complete and detailed sensor data. While the EEG signal quality is comparable to a state-of-the-art system, the number of channels is limited to 8. For this study, we have tested the device's real-time processing capability for SW phase targeting during NREM sleep. However, the system can be customized for many other research applications (e.g. real-time spindle detection or real-time tracking of wake brain oscillations in humans). A more integrated, wearable system is currently under development that will provide new opportunities for the assessment and intervention of sleep and EEG based research in real-world settings over sustained periods of time.

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