Validation of in-ear EEG for Sleep and Hearing Use Cases

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ABSTRACT

In-ear EEG (electroencephalography) is a recent development in EEG technology and could potentially be used to enable non-intrusive EEG recording in natural environments for extended periods, which is currently not possible. This white paper presents a comprehensive overview of a series of experiments conducted on a total of 26 participants to validate the IDUN Guardian’s capability of measuring EEG and other electrophysiological signals in the context of the relevant use cases: hearing and sleep. We validated the IDUN Guardian against a full-scalp EEG (mBrainTrain), an eye tracking device (PupilLabs), and a motion tracking system (Motive Tracker). The findings from these experiments show that the IDUN Guardian compares favorably against these gold standard systems. Firstly, results from the sleep use case show that the IDUN Guardian is able to accurately capture sleep stages as compared to full-scalp EEG data. Secondly, results from the hearing use case show that the IDUN Guardian is able to reliably measure neuronal processes of the auditory cortex and EOG (electrooculography) signals. While improvements are being made in both hardware and software, the IDUN Guardian is a significant advancement in making in-ear EEG technology accessible for widespread use in the consumer market.

1. Introduction

EEG, or electroencephalography, is a well-established non-invasive technique that measures brain activity by detecting the electrical signals produced by the brain (Nunez and Srinivasan 2007). This technology is beneficial for both clinical and consumer applications because it provides real-time measures of brain activity that can be turned into actionable insights. The main benefits of EEG are its non-invasive nature and the fact that the hardware can be miniaturized (Kim et.al 2022). Additionally, unlike other brain imaging techniques, such as fMRI or PET, EEG does not require the use of ionizing radiation or injection of contrast agents. This makes it safe to use in a wide range of populations, including children and pregnant women.

The preferred method for measuring EEG signals is by recording the EEG in a shielded laboratory and preparing the subject's skin prior to electrode placement to lower impedance. To prepare the skin for EEG recording, dead cells are removed from the top layer of the epidermis through abrasion and cleansing. This reduces the skin-electrode contact impedance. Electrodes with conductive gel are then applied. However, this process can be uncomfortable and painful for the patient and the gel causes skin irritation in many subjects. Care must be taken to prevent bridging between electrodes in high density montages, and the conductive paste may dry out over time, increasing contact impedance. Proper EEG recordings require a trained technician for both gel application and maintenance throughout the measurement. However, these standard procedures impede the usability of EEG devices and restrict their use outside the laboratory. Additionally, when it comes to real-world applications, the wired connections from the electrode cap to a computer can greatly restrict a subject's mobility and decrease their willingness to use it.

In recent years, there have been several advances in wearable technology, including the miniaturization of hardware, ultra-low power electronics, and increasing computational power and connectivity that make it possible to create comfortable and discreet wearable devices (Lee et al. 2016). Additionally, there have been significant improvements in the technology used in wearable devices such as the development of new types of sensors that can measure a wider range of physiological data. In-ear EEG sensors are small, discreet, and indistinguishable from regular consumer earbuds, making them well-suited for use in hearable devices. They can be used to measure a wide range of brain signals, and physiological signals including eye movements and muscle activity (Looney et al. 2012; Kidmose et al. 2013). Sleep monitoring based on in ear-EEG devices is a promising alternative to PSG (polysomnography) for long-term monitoring of sleep stages (Mikkelsen et al. 2015). Thus, in-ear EEG systems aim to address the limitations of lab-based systems by providing user-friendly devices that are easy to wear and allow for long-term recordings in everyday life and have several potential applications (Kappel et al. 2018). When compared with conventional EEG, in-ear EEG provides significantly improved comfort and convenience for the user. Since the sensors are placed inside the ear, they are less obtrusive and already socially accepted for everyday use. In-ear EEG is also inclusive since it does not exclude populations with incompatible hair types. It should be noted that the primary disadvantage of in-ear EEG in contrast to full-scalp EEG is the loss of spatial resolution due to the low number of channels. Overall, the advantages of in ear-EEG make it a useful tool for applications such as studying sleep and wakefulness and monitoring brain activity in real-world environments

2. Overview of the IDUN Guardian

The IDUN Guardian is an end-to-end in-ear EEG solution for the acquisition, processing and interpretation of neural information in real-time. It records, processes, and interprets changes related to brain activity through the ear canal. Using conductive polymer ear tips, the change in biopotential signal is measured from one ear to the opposite ear. The IDUN Guardian enables mobile and ubiquitous measurements of EEG signals in situations where EEG measurements are impractical. It consists of hardware and software components as described below.

Hardware: The IDUN Guardian Earbuds (IGEB) consist of ear tips, earpieces, and a brainbox. The ear tips are attached to earpieces for the left and right ears and feature the DRYODE (™) material formulation optimized for comfort and data quality. Ear tips in three sizes (S, M, L) can be utilized to provide proper fit and electrical contact between the electrode and the skin of the ear canal. The earhook fits comfortably over the ear anatomy of a person to support the sensors such that motion artefacts can be reduced. The brainbox includes a battery and an amplifier to measure the biopotential difference between the separate earpiece electrodes.

Software: Our software is a cloud-based platform consisting of a Python SDK which allows the recording and downloading of EEG data. Moreover, it features a real-time LSL stream to synchronize the EEG data and build in-house experiments.

3. Use Case: Sleep

3.1 Background

To measure sleep and evaluate its quality, various sleep assessment methods have been developed, each with different sensing modalities and varying levels of information provided. In a review of sleep assessment methods by Tabar et al. (2021), the authors note that the gold standard for sleep assessment is manual scoring of polysomnography (PSG) recordings; the PSG system provides detailed information about brain activity, sleep stages, and sleep quality. According to the American Academy of Sleep Medicine (AASM), a PSG typically includes EEG, EOG (electrooculography), chin EMG (electromyography), leg EMG, airflow, respiratory effort, oxygen saturation, and body position. It is is typically conducted in a sleep clinic by trained technicians using multiple sensors and video. The data from these sensors is analyzed and categorized into different stages of sleep, including Wake, rapid eye movement (REM) sleep, and non-rapid eye movement (NREM) sleep, with NREM further divided into N1, N2, and N3. This process of categorizing each 30-second epoch of PSG data is called sleep staging or scoring and is mostly based on EEG, EOG, and EMG information.. The PSG is widely used for diagnosing and treating sleep disorders such as obstructive sleep apnea, REM-sleep behavior disorder, and periodic limb movement disorder. While PSG offers high-quality sleep assessment, it can be uncomfortable and disruptive to sleep, which affects the accuracy of the measurement. Additionally, PSG is costly, requires clinical admission, and has long waiting lists, limiting its availability outside of specialized clinics. Furthermore, manual analysis and scoring of sleep data from PSG traces is time-consuming and can take a professional up to four hours to analyze an entire night's sleep.

3.2 Methods

An investigation was conducted to evaluate the IDUN Guardian alongside gold standard PSG during states of drowsiness and sleep. The hypothesis was that changes in brain activity indicative of sleep onset and awake states can be determined using in-ear EEG electrodes similar to standard scalp electrodes. The primary objective of this investigation was to evaluate whether the IDUN Guardian can be used to detect sleep onset as defined by gold standard PSG. Twelve healthy adults volunteered to participate in the study after signing the consent form and undergoing the mandatory screening. Subjects were monitored using the different components of conventional PSG: a full scalp EEG device (standard surface electrodes), EOG, chin EMG (electromyography) and ECG (electrocardiogram). The IDUN Guardian earbuds were placed in each external auditory canal.

In the clinical setting, the Maintenance of Wakefulness Test (MWT) is used to objectively assess an individual’s capacity to remain awake while sitting quietly in a dark room and is the gold standard test to evaluate wakefulness and drowsiness. Four trials of the MWT were conducted in this study, each lasting maximally 40 minutes and trials separated by two hours. Prior to the MWT phase, subjects underwent a sleep restricted night which began at each subject's self-reported bedtime. After four hours the subject was allowed to sleep for four hours (represented in Figure 1). Sleep restriction consisted of monitored, low-activity behaviors (anything that does not require too much physical activity such as reading a book or watching TV) and using electronic devices was not permitted during the final hour.

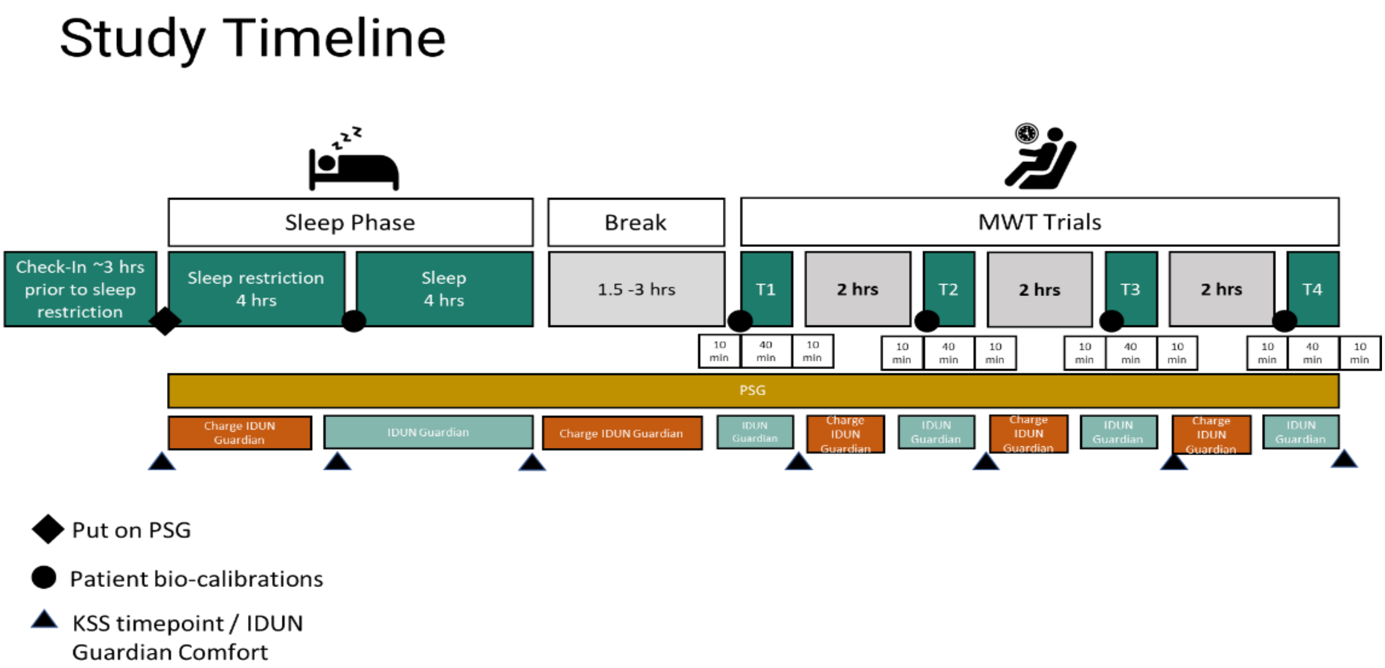


Figure 1 Timeline of the sleep study including the nighttime sleep phase and daytime MWT trials

3.3 Results

Signal Comparison

To assess the performance of the IDUN Guardian, signal quality of scalp-EEG (channel O2) and in-ear EEG recordings were compared by visually investigating the time-series signals. Further, a time-frequency decomposition was performed to evaluate and compare each recording based on the distribution of signal power across frequency bands. A spectrogram from a sleep recording of a single subject is depicted in Figure 2.

For signal evaluation, typical EEG sleep markers such as alpha waves, sleep spindles, K-complexes, and slow-wave sleep were taken into account. Overall, a good match between scalp and in-ear EEG data was observed. Out of a total of 60 datasets (12 subjects * [1 overnight recording + 4 MWT trials]) only 2 were excluded due to a high noise level in the IDUN Guardian signal. Two more datasets were excluded due to technical problems with the recording, leaving a total of 56 datasets that were analyzed and manually scored.

A representative comparison between the PSG and IDUN Guardian signals is shown in Figure 3 and Figure 4 where differentiation between the sleep architecture features (spindle, K-complex, and micro arousal) required for sleep staging (N2 in this case) can be clearly discerned.

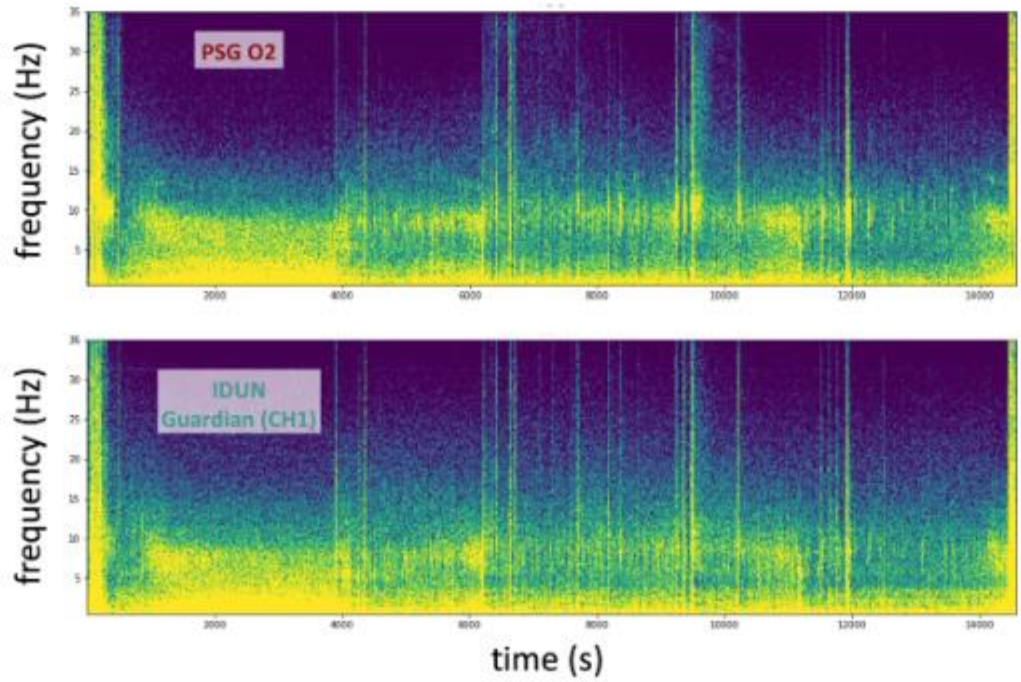


Figure 2 Comparisons of time-frequency decomposition between PSG channel (EEG O2) and IDUN Guardian reveal a strong match across different frequency bands throughout the recordings. In addition, shifts between sleep stages can be observed. Depiction of a single-subject overnight recording.

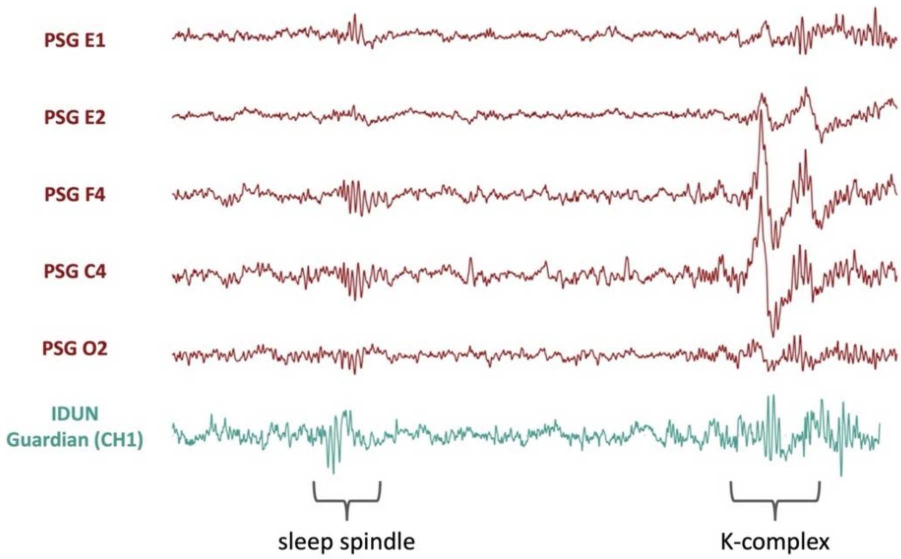


Figure 3 Single-subject signal comparison between PSG and IDUN Guardian recording. Visible sleep spindles and a K-complex as typical sleep markers for N2 sleep stage. Note that the slight shift in timing are likely due

to an imprecision in synchronization of the recordings.

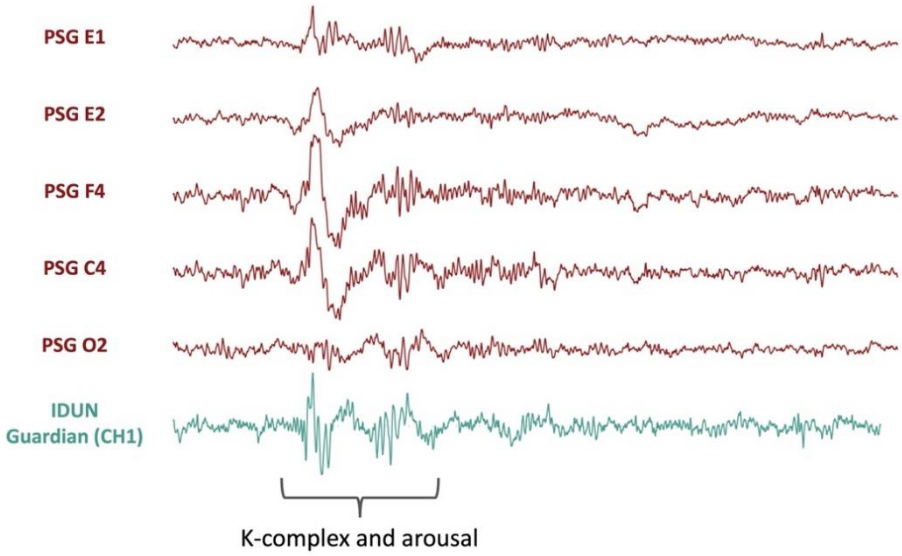


Figure 4 Single-subject signal comparison between PSG and IDUN Guardian recording. K-complex followed by a short arousal during N2 sleep stage. Note that the slight shift in timing are likely due to an imprecision in synchronization of the recordings.

With a focus on transition phases between sleep and wakefulness during the visual comparison of the signals, it was found that in most recordings, markers of these transitions could be reliably detected from the IDUN Guardian in-ear EEG channels. Examples of the alpha / theta transitions which define awake and sleep transitions are shown in Figure 5 (awake-sleep) and Figure 6 (sleep-awake). A microsleep example is shown in Figure 7.

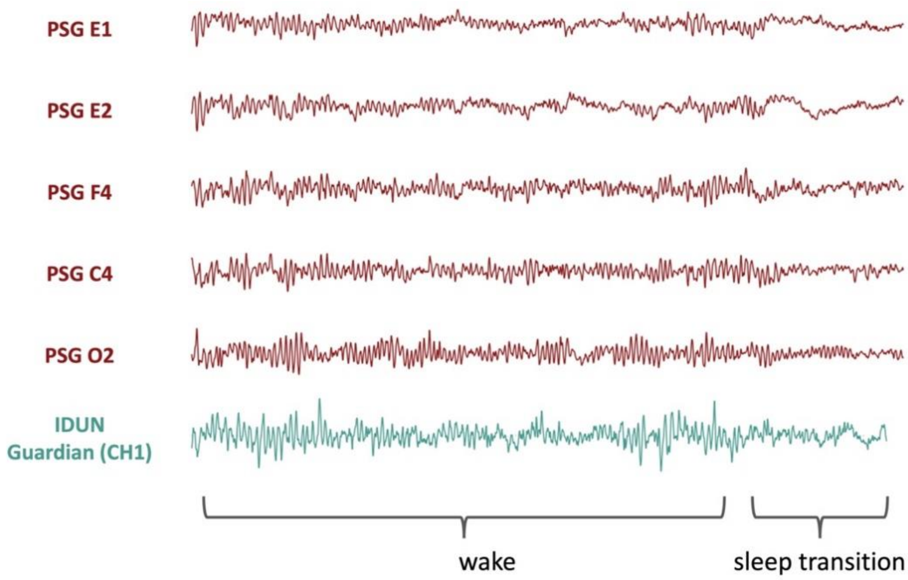


Figure 5 Single-subject signal comparison between PSG and IDUN Guardian recording with focus on sleep transitions. Clear alpha activity can be seen in all channels with a transition to light sleep at the end of the epoch visible by the disappearance of alpha and stronger occurrence of theta activity. Note that the slight shifts in timing are likely due to an imprecision in synchronization of the recordings.

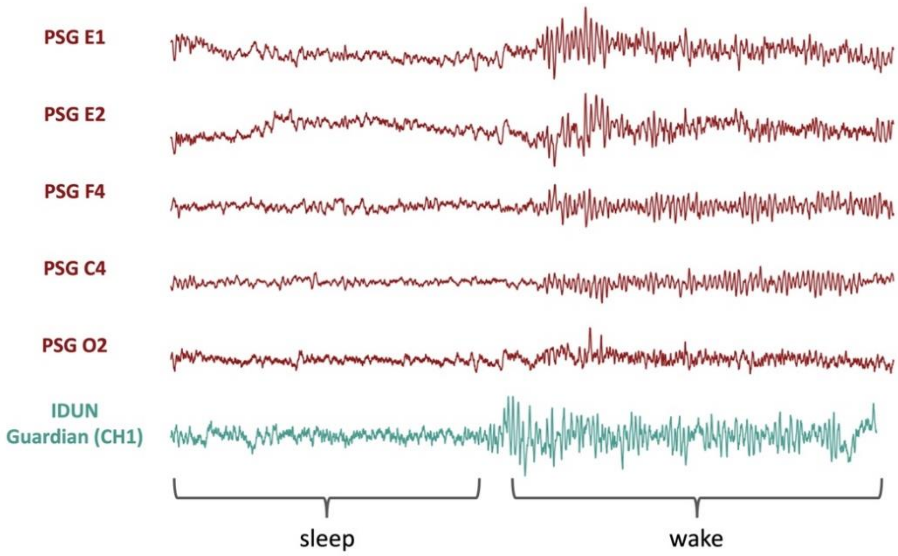


Figure 6. Single-subject signal comparison between PSG and IDUN Guardian recording with focus on sleep transitions. Transition from sleep to wakefulness visible in all channels by the shift from lower frequencies (i.e., theta) to pronounced alpha waves. Note that the slight shift in timing are likely due to an imprecision in synchronization of the recordings.

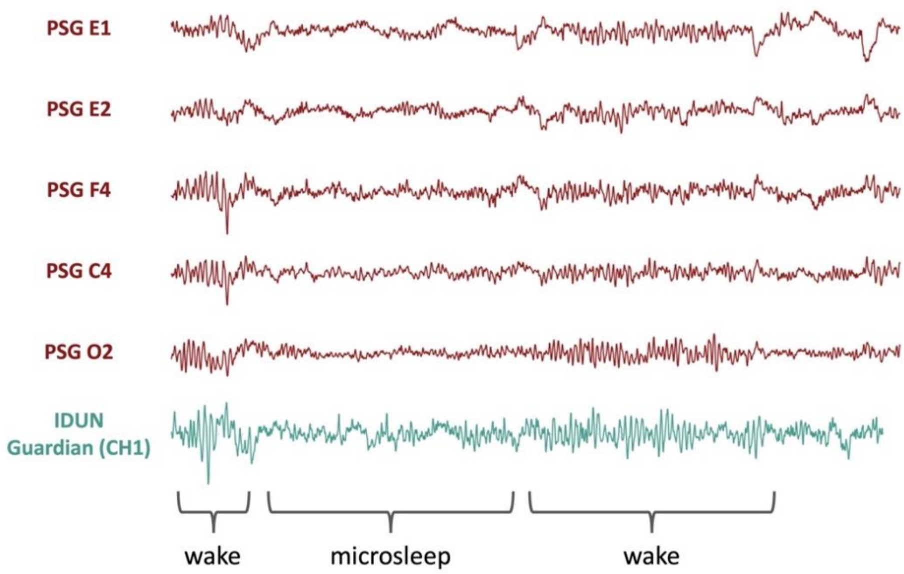


Figure 7. Single-subject signal comparison between PSG and IDUN Guardian recording with focus on sleep transitions. Epoch with occurrence of microsleep during period of sleep onset. Note that the slight shifts in timing are likely due to an imprecision in synchronization of the recordings.

Sleep Staging

Pre-processed, synchronized, and anonymized PSG and in-ear EEG data were scored separately by a single sleep scorer following AASM standards. Since the goal of this study was to evaluate the IDUN Guardian's performance to distinguish between awake and asleep, we combined all sleep stages (N1, N2, N3, and REM) to a single "asleep" score for further analysis. The overall scoring agreement between PSG and in-ear EEG recordings across 12 participants and 56 datasets was 0.68 (Cohen's Kappa) implying a good agreement. Figure 8 depicts agreement values for each of the recordings. Most values surpass the success threshold, and only 12 scoring agreement values remained below 0.6. Cohen's kappa coefficient is a statistical metric to evaluate rater reliability for categorical data and is widely used to assess inter- and intra-rater agreement of scorings in sleep research. It is thought to be robust because it takes into account the probability of the agreement occurring by chance.

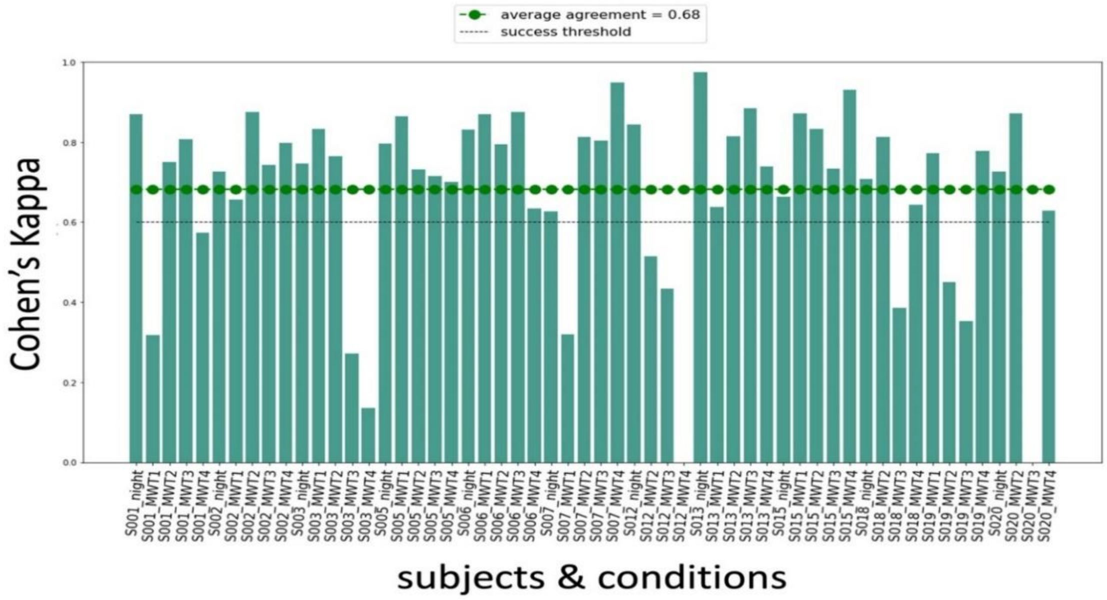


Figure 8. Scoring agreement ("awake" vs. "asleep") across all recordings. The success threshold of 0.6 was surpassed by the majority, implying that the IDUN Guardian in-ear EEG data can be used to reliably distinguish between sleep and wakefulness.

3.4 Discussion

The goal of this study was to evaluate the ability of the IDUN Guardian to distinguish between stages of sleep and wakefulness and to validate its potential to detect EEG markers characteristic of sleep onset and stage transitions. However, based on this result, it would be logical to assume that the agreement of 0.68 in the Cohen's Kappa results would have been higher (

Figure 8). One reason for this inconsistency may reside in the sleep scoring and data synchronization approach.

There are two factors that could potentially affect the IDUN Guardian scorings compared to PSG scorings that should be addressed:

- Firstly, the PSG signal provides generally more information than the IDUN Guardian signal, so while the decision to assign sleep stages to different epochs in PSG data can be based on information from multiple sources (multiple EEG regions, EMG, ECG and a distinct EOG), the IDUN Guardian so far only offers an EEG signal from one location and indication of horizontal eye movements.
- The second factor is that because there is only one location where data is being recorded from in the IDUN Guardian setup, introduced noise in this area (e.g., due to high impedance or bad skin contact) might have a larger impact on the scored result compared to the PSG setup.

With regard to the sleep staging discrepancies, the AASM standard defines sleep staging rules based on signal features that are captured in 30 second epochs of the EEG signal. Therefore, a misalignment of signals between the PSG and IDUN Guardian device means that even though they may individually capture the same sleep-related EEG signal features, the sleep staging results may be different since epoch would be scored out of sync with one another and the full sleep journey of the study participant.

4. Use Case: Hearing

4.1 Hearing intent based on eye gaze

4.1.1 Background

In addition to in-ear EEG, there has also been growing interest in measuring eye movement via the means of in-ear EOG systems (Favre-Felix et al. 2017; Favre-Félix et al. 2019; Hládek et al. 2018; Skoglund et al. 2022). As compared to eye tracking devices, in-ear EOG sensors are more unobtrusive and enable the recording of EOG signals from the ear canal. Eye movement (or eye gaze) detection would be a valuable integration in hearing aid devices e.g., steering directional microphones towards attended sounds which would enable impaired listeners to engage in dynamic conversations in noisy environments (Favre-Félix et al., 2018). In addition, eye movement information has been linked to health and mental state in humans; in this regard, previous studies found a correlation between eye movements and different types of neurodegenerative diseases (Anderson and MacAskill 2013). This consequently opens new avenues in real-time monitoring of health-related aspects of a user based on changes in eye movements.

4.1.2 Methods

In a series of experiments, the feasibility of the IDUN Guardian in-ear sensor technology was investigated and tested. Specifically, we validated the device in terms of its capability to measure reliable neuromarkers (brain responses to auditory stimuli through electroencephalography (EEG)), as well as other electrophysiological signals (e.g., eye movement as measured with in-ear electrooculogram (EOG)). Fourteen healthy subjects with no hearing impairment were recruited for the study. Two subjects were excluded, one due to having tinnitus and the other due to small ear canals where the in-ear sensor did not fit. The remaining population of 12 subjects [3 female, 9 male; age mean: 30.1 years, range: 18-60] participated in the study.

Technical Setup

During the recording of the experiments, multimodal data was measured to investigate body/shoulder movement (motion tracking using Motive Tracker; OptiTrack), head movement (Smarting Pro, mBrainTrain), eye movement (Pupil Labs Eye tracking), and brain activity (Smarting Pro, mBrainTrain; IDUN Guardian). In particular, the motion tracking devices were attached on each subjects' shoulders (left and right). Here, 5 markers were used on each side to create rigid body for the tracking of the left and right shoulder, respectively. Data streams were time-synchronized using Labstream Layer (LSL) network protocol based on the setup illustrated in Figure 3. Table 1 summarizes each system used with the number of channels and the sampling rate.

Impedance Measurements

Impedances for both the IDUN Guardian as well as the full-scalp EEG electrodes were measured at the same time when comfort was assessed (i.e., before each experiment block). Note that substantial differences in skin-electrode impedance are to be expected when comparing wet (i.e., using conductive electrolyte gel) and dry electrode systems. Pupil detection confidence was verified in between experimental blocks.

Technical equipment and the corresponding data streams			
		Number of channels	*Sampling rate [Hz]*
IDUN Guardian in-ear sensors		*2*	*250*
Smarting Pro	*EEG*	*24*	*250*
	EOG	*2*	*250*
	Accelerometer Gyroscope	*6*	*250*
Eye Tracking (Pupils Lab)		*22*	*7.25*
Motion Tracker (Motive Tracker)		*12*	*60*
Marker stream (Psychopy)		*1*	*-*

Table 1 Summary of the different systems used during the study

Procedure

In the first set of experiments, we investigated human movement behavior during a simple auditory attention task, aiming to gain insights into the relationship between body, head, and eye movement. This first block was subdivided into 3 smaller experiments (1a, 1b, and 1c). In all these experiments, participants were stood approximately 2 meters apart from three screens, a left, middle, and right one (Figure 9). Each experiment consisted of 10 trials. Prior to each trial, participants were instructed to shift their attention to either a female or a male speaker, displayed on either the right or left screen. The respective audio tracks were played via speakers positioned behind the left and right screens. In each trial, both speakers were speaking simultaneously for 10 seconds. After that, participants had to focus on the middle screen again and wait for the instructions for the next trial. The setup in all these three experiments was therefore very similar. What differed from experiment to experiment was the allowed freedom of movement. Every experiment started with a test trial to ensure that participants understood the procedure. In Experiment 1a, participants were allowed to freely move their upper body, head, and eyes to turn their attention to the intended speaker, but they had to stay in place. In Experiment 1b, we aimed to investigate the correlation between head and eye movements. They were instructed to fully turn their head to the intended speaker so they would look directly at him/her throughout each trial. To further disentangle head and eye movements, participants were instructed to close their eyes during the Experiment 1c. Before each trial, they were told by the experimenter which speaker they needed to focus on.

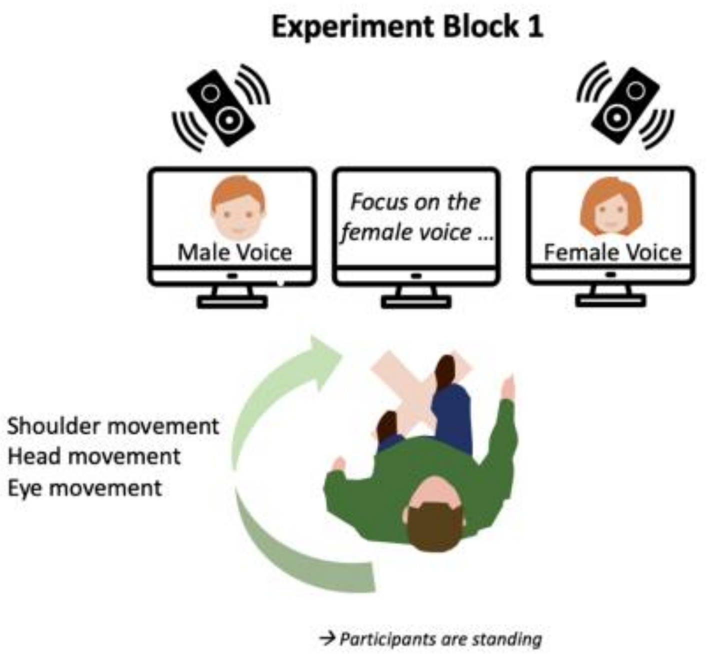


Figure 9. Depiction of the experiment block 1. In each trial, participants were instructed to pay attention to the male or female speaker.

4.1.3 Results

Data Preprocessing

To investigate the research questions detailed above, comprehensive preprocessing of the multi-modal streams was required to ensure that they are comparable to each other. This was done by first converting the different streams of interest to categorical numbers defined as left (-1), center (0), and right (1).

The processing steps are listed below for each stream individually:

Marker stream

The marker stream corresponds to the ground truth. The timestamps of the marker stream were adapted using the IDUN Guardian time stamps as a reference. The marker stream was converted to categorical numbers as mentioned above.

Motion tracker stream

The motion tracker stream corresponds to the tracking of shoulder movement. The marker's time stamps were replaced with the closest IDUN Guardian time stamps which were used as the base. All data before and after the first and last time stamps were removed and the "yaw_right" channel of the motion tracker stream (placed at the right shoulder) was utilized. The data were detrended to remove DC drift and then divided by its standard deviation. After removing outliers, data were bandpassed filtered (highpass: 0.5 Hz, lowpass: 5Hz). Finally, the data were manually adapted and sorted according to the two thresholds as shown in Figure 10.

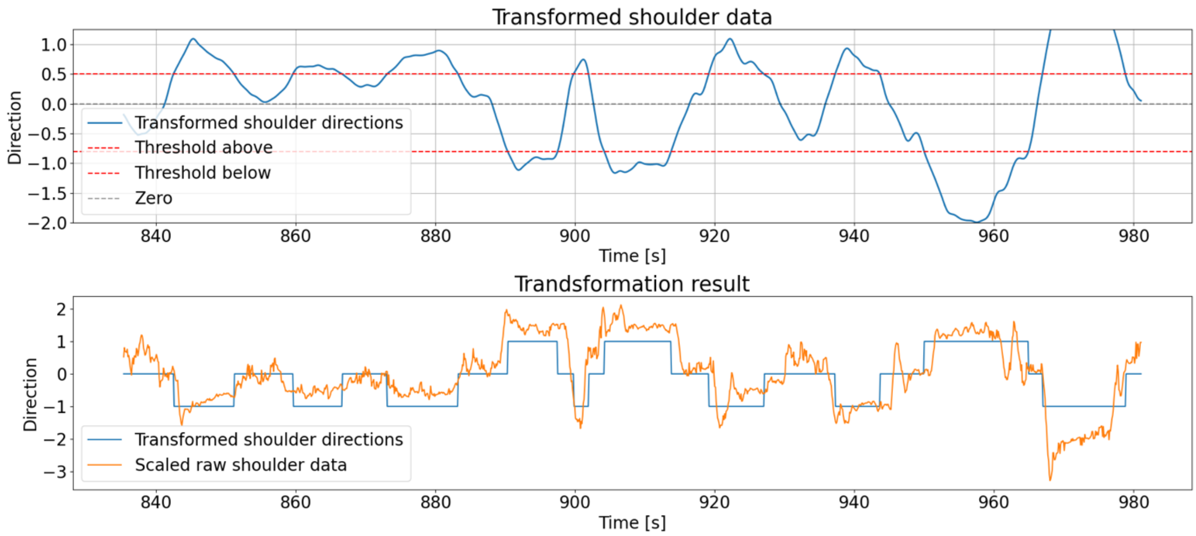


Figure 10: Preprocessing of the motion capture data. In the upper figure, the blue curve represents the raw motion capture data ("yaw right shoulder") with an example of the individually chosen thresholds to categorize left, right and center. The lower figure (inverted) shows the scaled and transformed data that is used to compare to the other data streams.

Eye tracker

The eye tracker measures the eye movements. The eye data's time stamps were replaced with the closest IDUN Guardian time stamps which were used as the base. All the data before the first- and last-time stamps were removed. The "norm_pos_x" channel of the eye tracking device was utilized. The data was detrended to remove the DC drift after which the dataset was divided by its standard deviation and outliers were removed. The data was smoothed using a smoothing window of 5 samples. Finally, the data was manually adapted and sorted according to the two thresholds as shown in Figure 11.

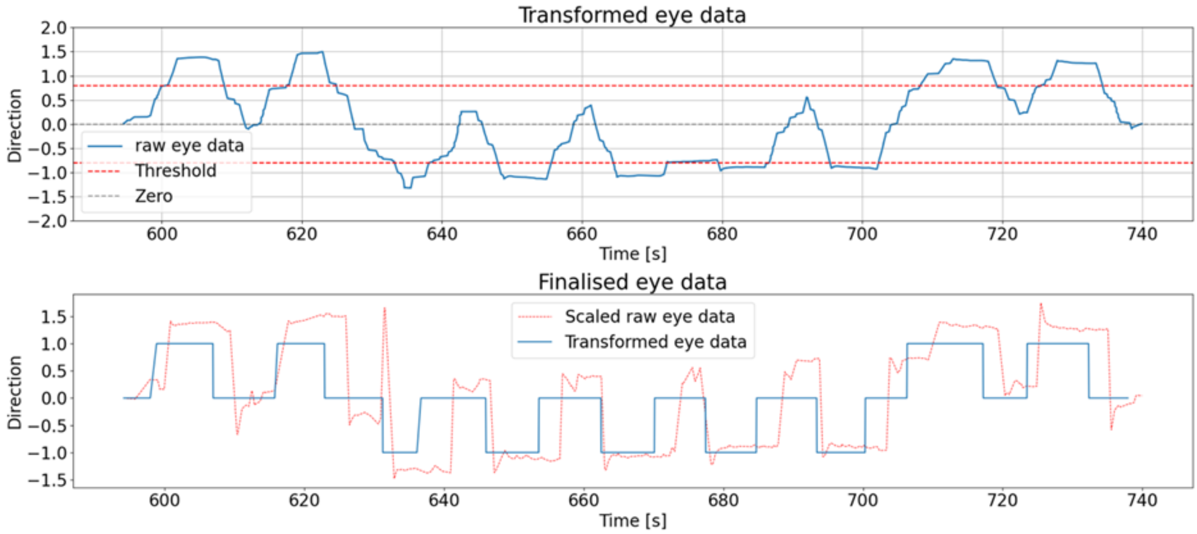


Figure 11: Preprocessing of the eye tracking data. In the upper figure, the blue curve represents the raw eye tracking data with an example of the individual chosen threshold to categorize left, right and center. The lower figure shows the scaled and transformed eye tracking data which is used to compare to the other data streams

Gyroscope

The gyroscope tracks the head movement measurements. The gyroscope data's time stamps were replaced with the closest IDUN Guardian time stamps which were used as the base. All the data before the first and last time stamps were removed. The "GyroZ" channel of the mBrainTrain EEG device was utilized. The data was detrended, normalized, and outliers were removed. The data points were looped through the accelerometer data and then summed to create an accumulative array providing an estimate of the absolute head direction. Finally, the data was manually adapted and sorted according to the two thresholds as shown in Figure 12.

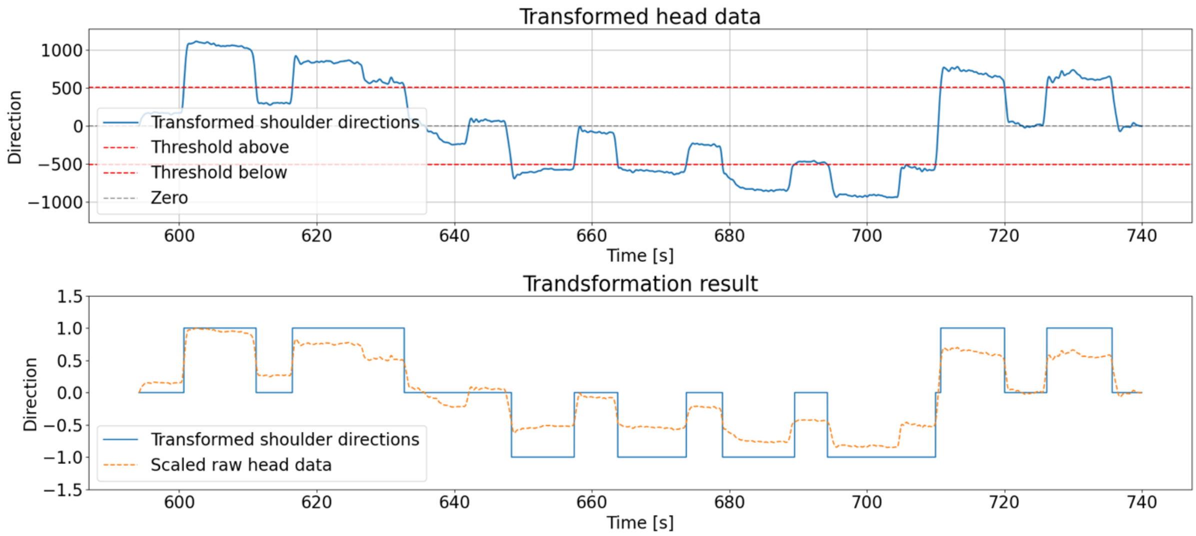


Figure 12: Preprocessing of the eye tracking data. Upper figure, blue curve represents the raw eye tracking data with an example of the individual chosen threshold to categorize left, right and center. Lower figure, shows the scaled and transformed eye tracking data which is used to compare to the other data streams

After performing the multimodal data processing, we proved the validity of the in-ear EOG use case

1. by measuring the temporal relationship between shoulder, head, and eye movement during active rotation towards the auditory sound source (e.g., towards the female voice after fixating on the center screen).
2. by testing the in-house built (binary) eye movement classifier and investigating its performance for different movement scenarios. In addition, we used the eye tracking data as ground truth for labeling the absolute direction (left, right) of eye movements.

In experiment Block 1, investigation of the relationship between movement-related physiological signals from the shoulder (measured with the motion capture system), head (measured with the gyroscope integrated with the full-scalp EEG system), and eyes (measured with the eye tracking device) was investigated. It was found that the onset of eye movement across subjects and trials was about 30% - 35% faster compared to the onset of head and shoulders. Here, after stimulus onset, the eye movement appeared, on average, 1.03 sec. (std: ± 0.74 sec.), the head movement with a mean onset of 1.64 sec. (std: ± 0.47 sec.) and the onset of shoulder movement was, on average, 1.6 sec. (std: ± 0.89 sec.).

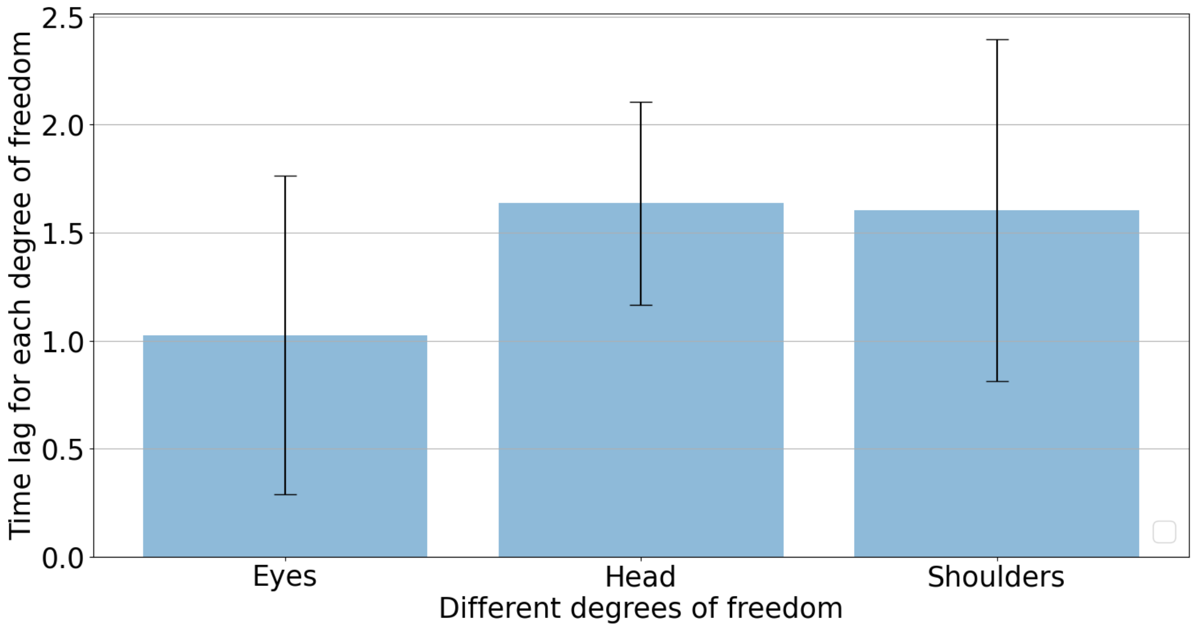


Figure 13: Latencies in seconds after stimulus onset for each movement-related physiological signal for eye movement (measured via eye tracker), head movement (measured with the gyroscope of the full-scalp EEG system), and shoulder movement (measured with the motion capture system).

The eye movement classifier's performance under natural movement was tested (using the active rotation of the head, shoulders, and eyes), meaning with no restrictions. The results showed a mean classification accuracy of 78.12% [std: ±12.92%] across all trials and participants, see also Figure 14. Furthermore, in the condition of restricting shoulder movement and only allowing for head and eye movement, the classification accuracy was found to be similar or slightly better with 80.67% [std: ± 17.71%]. Lastly, these results were compared with the condition of restricting shoulder and head movement and only allowing eye movement. The classification accuracy was 82.12% [std: ±12.32%]. *Note*: In all three cases our classifier used for generating the predictions was uncalibrated meaning that it assumed a fixed threshold across all subjects in detecting left and right eye movement. As such, a calibrated classifier was also tested (calibration has been performed using the baseline data acquired at the beginning of the experiment prior to starting experiment block 1). The calibration essentially aimed to determine subject-specific hyperparameters and was used to inform the classifier. Here, the performance of the calibrated classifier was slightly better (increase in performance by 1-2%) in comparison to the uncalibrated version.

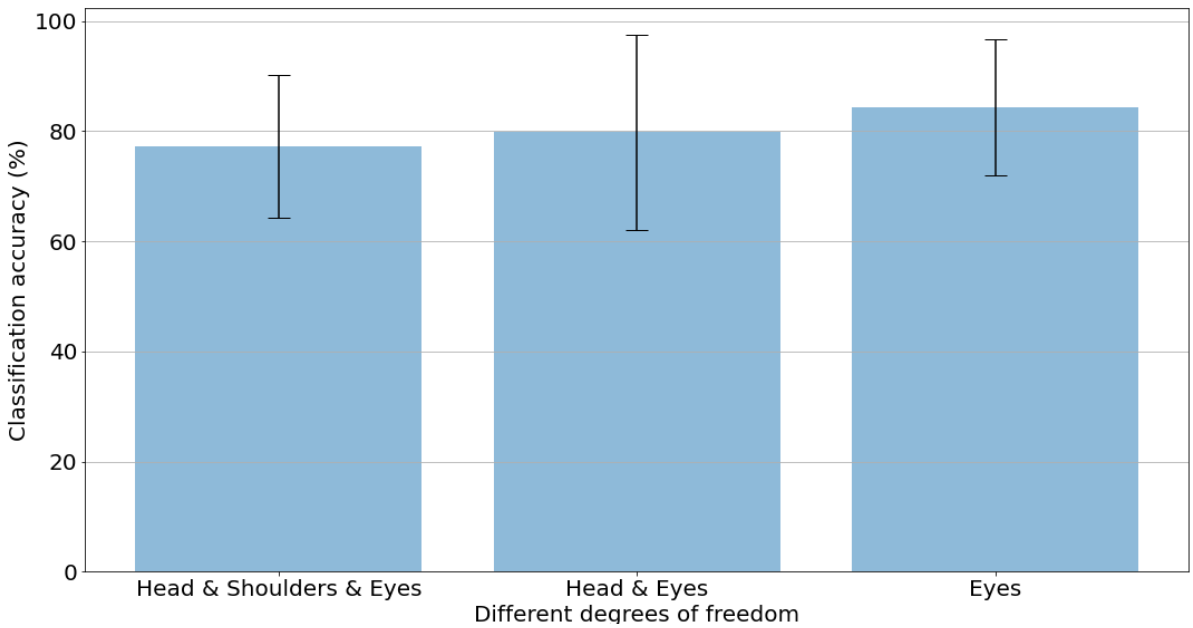


Figure 14: Results of the classification accuracy of the uncalibrated (group-level derived hyperparameters from pooled eye movement datasets) eye movement classifier for different conditions

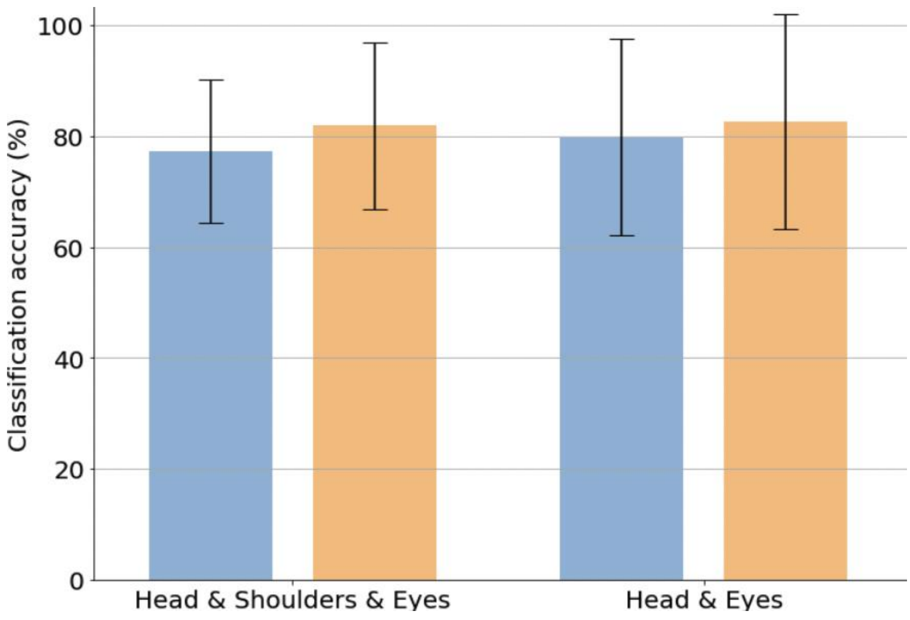


Figure 15: Eye movement detection results of the uncalibrated (blue) and calibrated (orange) classifier during the natural (head and shoulder) vs. head-only movement.

4.1.4 Discussion

Validity of in-ear EOG and real-time eye movement detection

In this experiment, the feasibility and usability of the in-ear EOG system towards real-world usage were demonstrated. Under different (quasi-) realistic conditions, specifically decreasing the degrees of freedom of active movement, we investigated how eye, head and shoulder movement interact during a stationary (in standing position) rotation task. Here, participants were instructed to rotate their upper bodies to the speaker's voice. One key observation was the temporal decoupling of eye movement from the head and shoulder movement. In general, this observation indicates that the eye movement detection would not be severely affected by the head and shoulder movement Figure 24, again, illustrates that the EOG signal pattern (bandpassed between 7-15 Hz and here scaled for comparison with the shoulder and head movement data) from the IDUN system (IDUN Guardian) is clearly noticeable. The classification performance (both for the uncalibrated and calibrated) results confirm that head and shoulder movement do not drastically decrease overall detection rate.

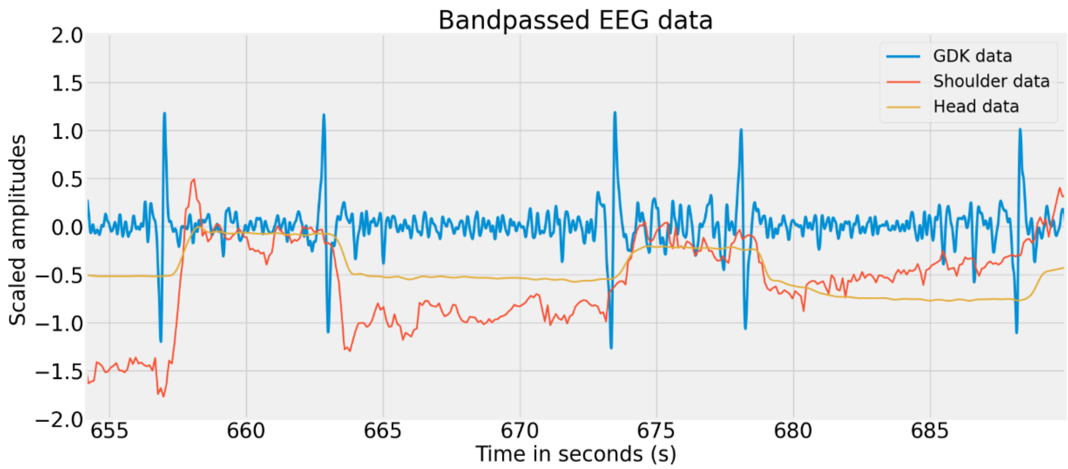


Figure 16: Sample of time-synchronized data streams of the IDUN Guardian, motion, and head tracker. IDUN GUARDIAN data is band-passed (7-15 Hz) and scaled to compare with the shoulder and head tracking data.

Computational efficiency of the real-time eye movement classifier

The current implementation of the eye movement classifier enables binary classification between left and right eye movement. Here, one distinguishes between uncalibrated and calibrated phases where the former uses group-level derived hyperparameters (pooled over hundreds of eye movement datasets). The latter uses user-adapted parameters allowing for personalized eye movement profiles. Earlier it was observed that the accuracy of the calibrated one was slightly better than the uncalibrated version. Currently, the adaptation of subject-based signal characteristics is heuristic and, therefore, has plenty of room for optimization, e.g., to include model-based learning of relevant EOG features.

Moreover, the classifier predicts the eye movement state per sample (given a sampling rate of 250 Hz, equivalent to predicting every 4 milliseconds) given a pre-defined buffer (with an array size of 250 samples) operating under first-in-first-out (FIFO) principle. Thus, the space complexity of the classifier is O(N) with a time complexity of O (1). The implementation of the classifier was done in Python. We have further estimated the computational time from input (sample going into the buffer) to the output (obtaining a prediction) with an average overhead of 130 microseconds (see Figure 25). The calculation of the latencies was performed on a Macbook Pro M1 chip (8-core CPU and 8-core GPU, 3.2 GHz), 16 GB RAM.

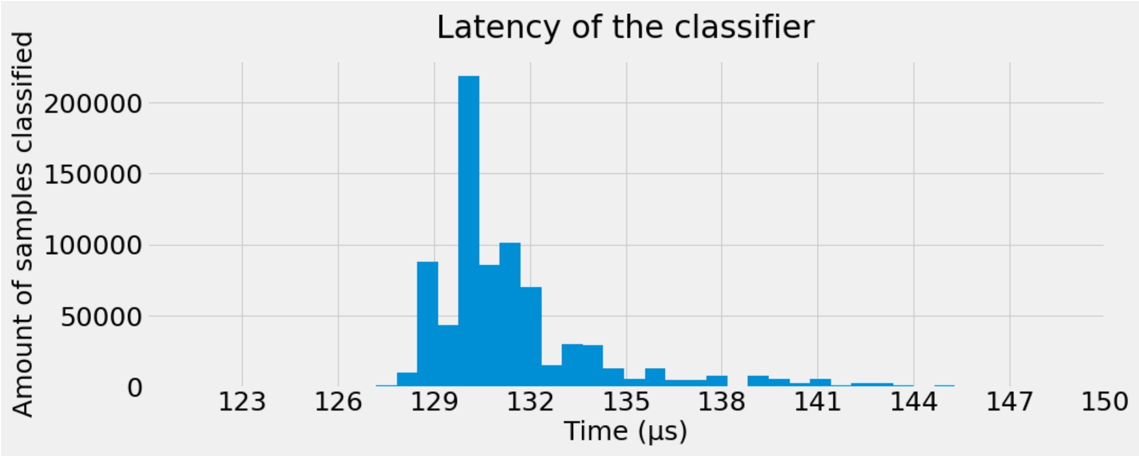


Figure 17: Computational time of the implementation of the eye movement classifier algorithm (in microseconds); from input sample to output prediction

Future extension of the in-ear EOG system

Future development of the eye movement classifier concerns its extension to detect angular differences to identify the user's focus of attention. Recent studies have successfully demonstrated absolute eye gaze estimation in real-time scenarios (Favre-Felix et al., 2017; Favre-Félix et al., 2019). However, the devices under investigation in these reports contained customized conductive molds fitted to each participant individually. This obviously hinders mass production of conductive ear tips and does not conform to an easy-to-get over-the-counter hearing aid product. On the contrary, the IDUN Guardian consists of a soft stretchable sensor that comes in universal standard sizes matching those sizes from current earbud product lines (e.g., Apple, Bose, Sony, etc.). Moreover, it will be interesting to extend current experiments by testing the usability of the eye movement classifier during active walking. To overcome walking-related artifacts, one could perform artifact rejection by including an inertial measurement unit (IMU).

Another potential extension or alternative (hardware-) solution of the in-ear EOG system would be to perform eye movement detection based on a single-ear (within-ear reference) EOG system. If the EOG signal characteristics are comparable to the one generated by the opposite-ear reference system, the corresponding eye movement classifier should theoretically perform similarly well. This can be very well tested in a future study.

4.2 Auditory signal decoding using in-ear EEG

4.2.1 Background

When it comes to hearing, previous studies have found that EEG is well suited to inform future hearing aid algorithms on a listener's focus of attention (Fiedler et al. 2017; Holtze et al. 2022). EEG signals could be used to adapt noise suppression algorithms or to align directional microphones to the attended sound source (as in the case with the in-ear EOG). Another way where EEG can be beneficial for enhancing hearing health is through the estimation of an individual's hearing threshold by frequency. This can be achieved by the presentation of a repetitive auditory stimulus provoking populations of neurons to fire synchronously at the frequency of the presented stimulus. This frequency-specific neuronal activity can be picked up by EEG and can be displayed in the frequency spectrum of the data. This is known the Auditory Steady State Response (ASSR) and could be used to personalize the hearing experience to an individual's unique hearing profile (i.e.smart equalizer).

4.2.2. Method

In the second set of experiments, we investigated auditory processing of the auditory steady-state response (ASSR) in different settings. Again, this experimental block was subdivided into three smaller experiments (2a, 2b, and 2c). In each experiment, participants had to stand and focus on a fixation cross in the center of the middle screen.

- In Experiment 2a, a single speaker was placed at different locations around the participant, always facing towards him/her, always at an approximately 1-meter distance, and always at the same height (approximately ear level) (see Figure 16A). At each location, the participant was presented with three 20-second trials of an auditory stimulus played at a 90 Hz repetition rate, played at a volume of approximately 70 dB SPL. In Experiments 2b and 2c, we investigated the neuronal responses to two concurrently presented auditory stimuli (one at an 85 Hz, one at a 95 Hz repetition rate) and the effect of attention on the measured ASSRs. In both experiments, participants were stimulated with the 85 Hz tone coming from their left side and the 95 Hz tone coming from their right side. In each trial, participants were asked to either focus on the stimulus coming from their left or right.
- In Experiment 2b, these stimuli were presented via headphones and the volume was set to 30% of the computer's maximal volume (approximately corresponding to 70 dB SPL). Each condition (left focus or right focus) was repeated 3 times and each stimulation lasted 20 seconds.
- In Experiment 2c, participants listened to the two concurrently played sounds via speakers. Similar to Experiment 2a, the location of the speakers changed throughout the experiment according to Figure 16B. At each location, each condition (focus left or focus right) was repeated 3 times, and each stimulation lasted 20 seconds. Again, stimuli were presented at approximately 70 dB SPL.

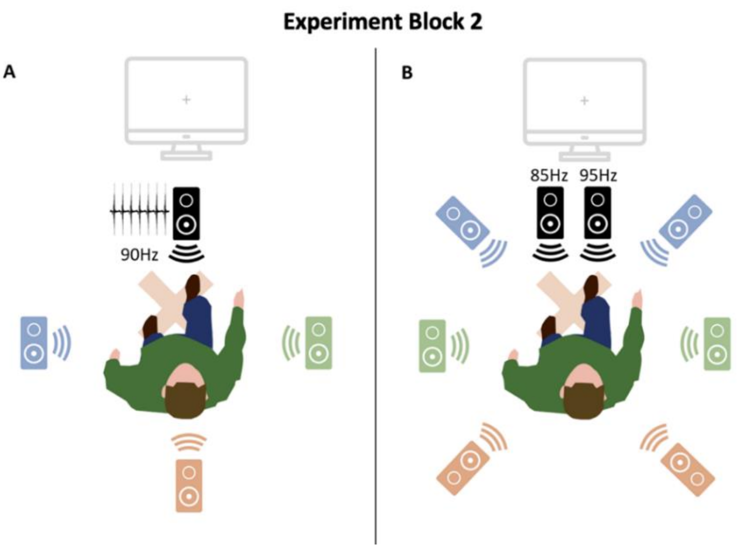


Figure 18: Setup for the experiments in Block B. Left: Experiment 2a and B: Experiment 2c. Speakers in different colors refer to different speaker locations.

4.2.3 Results

The main goal of experiment Block B was to investigate the ability to measure the neuronal processing of auditory signals with the IDUN Guardian and to compare these EEG responses to gold-standard full-scalp EEG data. For this, all EEG data were preprocessed by applying a narrow band-pass filter (± 4 Hz around stimulation frequency). To analyze the EEG response to the auditory stimuli, individual filtered data of each stimulation trial were Fourier-transformed (FFT) and averaged. The signal-to-noise ratio (SNR) was then calculated by extracting the peak amplitude at the stimulation frequency (± 1.5 Hz) and dividing it by the peak amplitude at the surrounding frequencies of the stimulation frequency (± 1.5 Hz – ± 3 Hz). The highest SNR value across all EEG electrodes was used to calculate the averages across participants for each EEG system.

Experiment 2a

Experiment 2a aimed to investigate the ability of in-ear EEG to measure neuronal responses to an auditory stimulus played from different locations around the listener. Auditory stimuli are known to mostly activate areas of the contralateral auditory cortex. This is confirmed by investigating the ASSR sources in the brain derived from full-scalp EEG data. If the speaker was placed on the person’s right side, the left auditory cortex responded stronger compared to the right, and vice versa (see Figure 17). Overall, the SNR values for both in-ear and full-scalp EEG highlight the ability of both systems to measure processes of the auditory cortex in response to a specific stimulus. Simultaneously, no speaker location showed preferred EEG activation as shown in Figure 18.

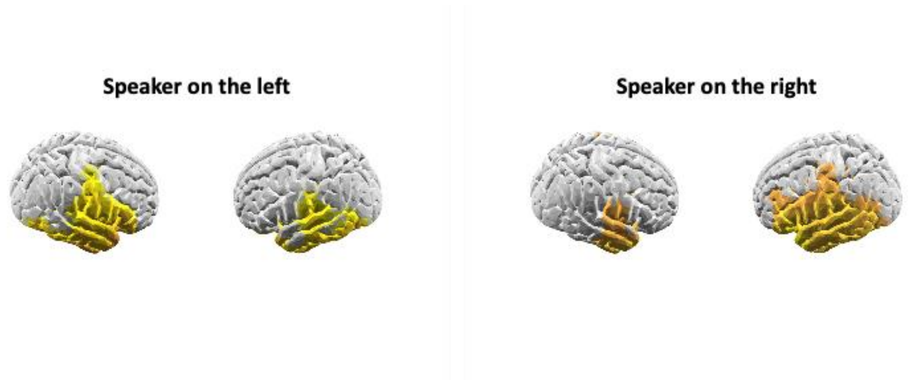


Figure 19: Source-localization from full-scalp EEG data reveals activation of the auditory cortices as a response to 90 Hz auditory stimulation. Depicted are 3D topographical representations of the EEG sources in an exemplary participant showing expected stronger contralateral ASSR responses to auditory stimulation from the left/right side.

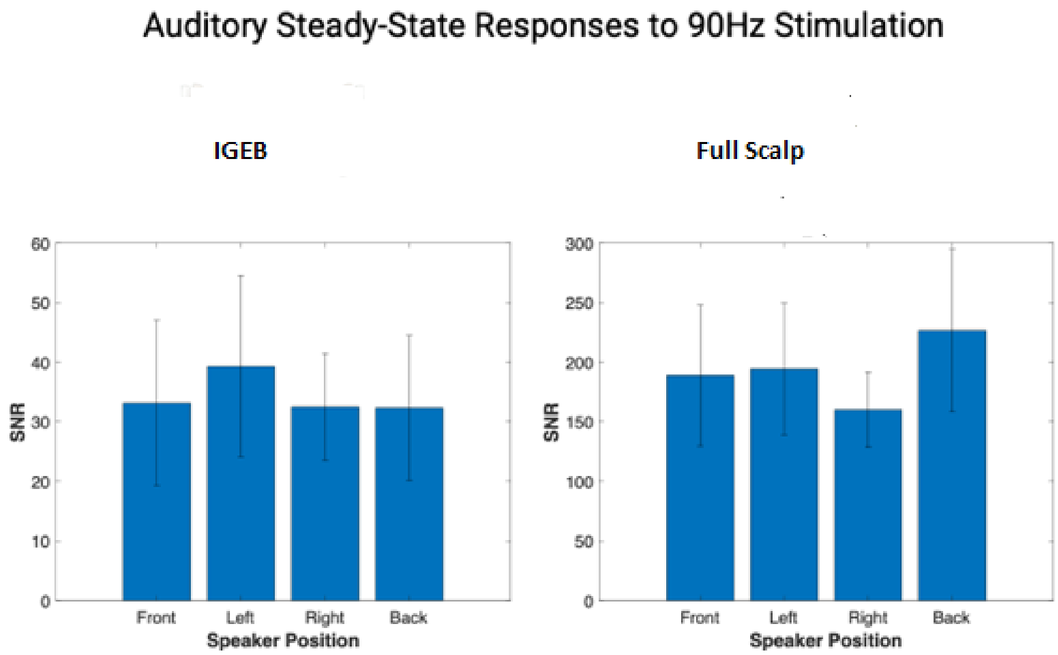


Figure 20: SNR values confirm a strong stimulus-specific response to 90Hz auditory stimulation in both EEG systems. As expected, stronger responses can be seen in the full-scalp EEG system compared to in-ear EEG (IDUN GUARDIAN). No significant differences in SNR values can be identified across the four different speaker locations.

Further analyses of the data revealed that in-ear EEG can measure a neuronal response to the 90Hz stimulation already within the first second after stimulation onset (see Figure 19). This result shows in-ear EEG's potential to measure real-time auditory processes of the brain with minimal latency.

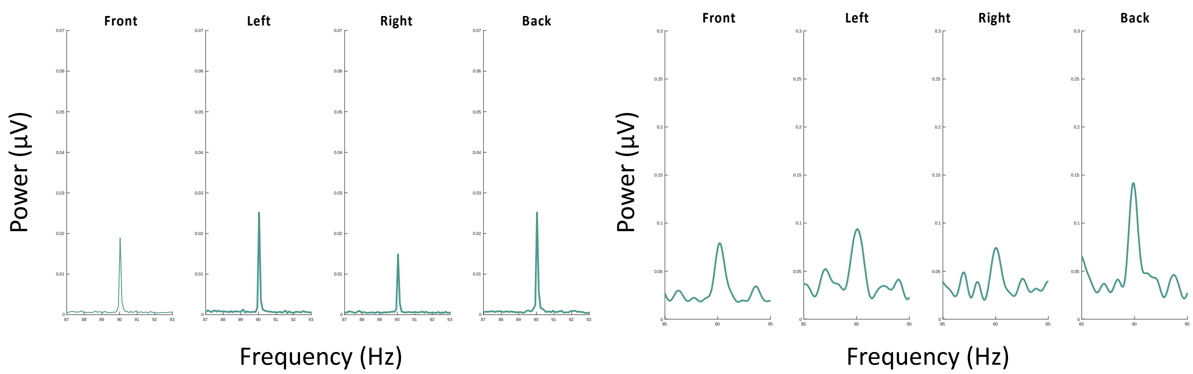


Figure 21: FFT responses to 90 Hz stimulation measured via in-ear EEG. Left: Responses to 20-second stimulation across four speaker positions; Right: Responses after the first second of the stimulation across four speaker positions.

Experiment 2b

During Experiment 2b participants were presented with two concurrently played chirp stimuli through headphones, see Figure 20. The stimuli were presented at repetition rates of 85Hz (left side) and 95Hz (right side). This experiment aimed to investigate the ability of in-ear EEG to measure neuronal responses to two concurrently played auditory stimuli and additionally, investigate the effects of a person's attention allocation on the neuronal responses.

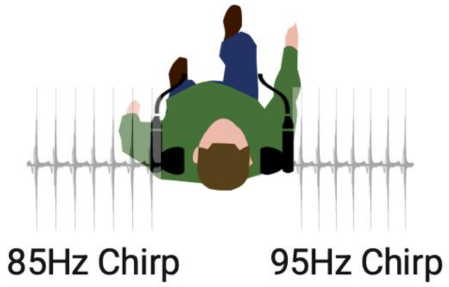


Figure 22: Depiction of the auditory stimulation design in Experiment 2b.

Confirming the results of Experiment 2a, both EEG systems (full-scalp and in-ear) reveal high SNR values across all participants. Furthermore, the depiction of FFT analyses shows that neuronal responses to both concurrently played stimuli can be measured through EEG (see Figure 21). However, no distinguishable difference in FFT amplitudes can be seen between the attentional allocation conditions.

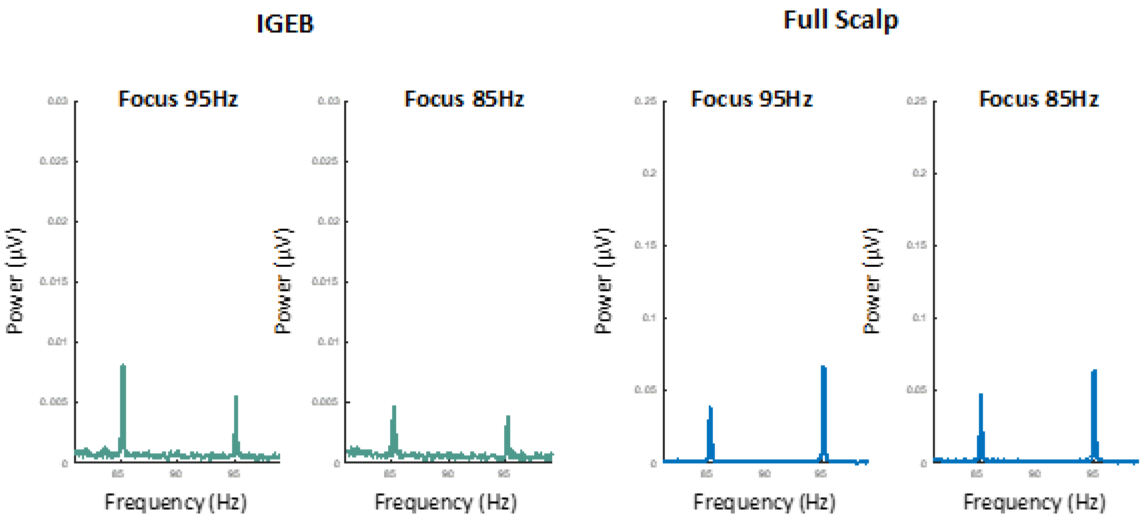


Figure 23: FFT of EEG responses to simultaneous 95Hz and 85Hz auditory stimulation across both attentional allocation conditions. Left: in-ear EEG; Right: full-scalp EEG.

Experiment 2c

Experiment 2c represents the combination of Experiments 2a and 2b. As in Experiment 2a, auditory stimulation was applied through speakers positioned at different locations around the participants (Figure 22). Like Experiment 2b, stimulation consisted of 2 concurrently played chirp stimuli with repetition rates of 85Hz (left speaker) and 95Hz (right speaker).

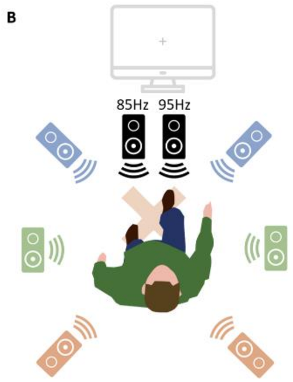
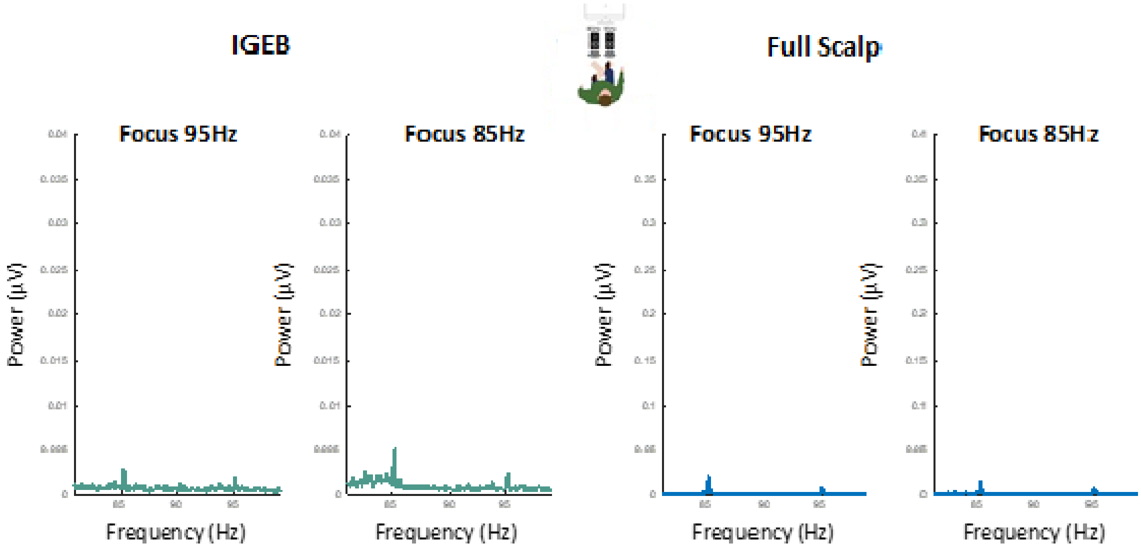
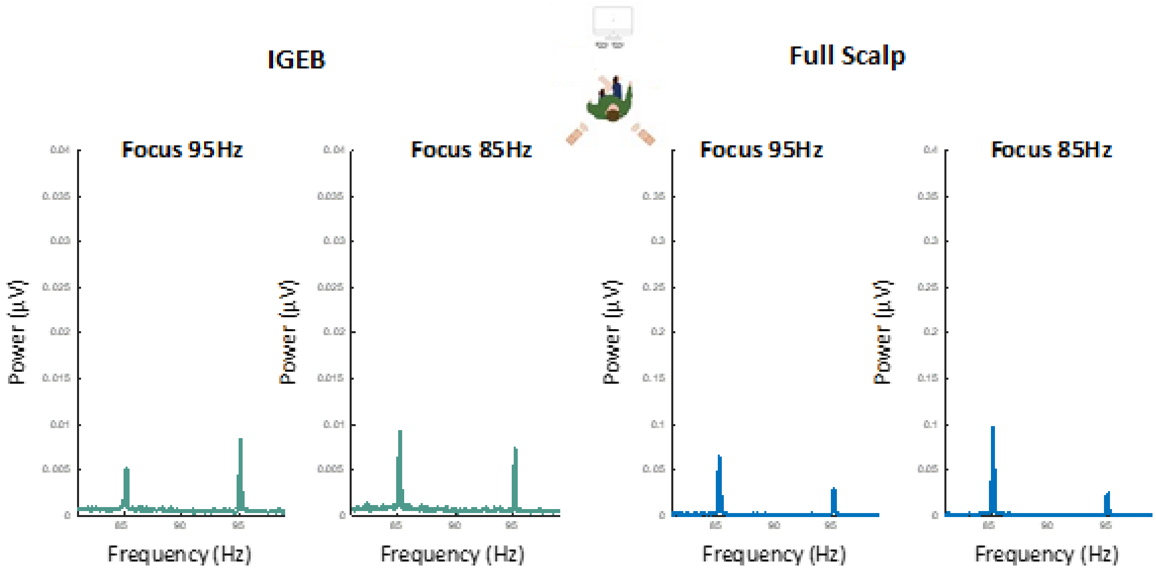


Figure 24: Depiction of the auditory stimulation design in Experiment 2c. Different colored speakers represent the different speaker locations.

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Full Scalp
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Power (µV)
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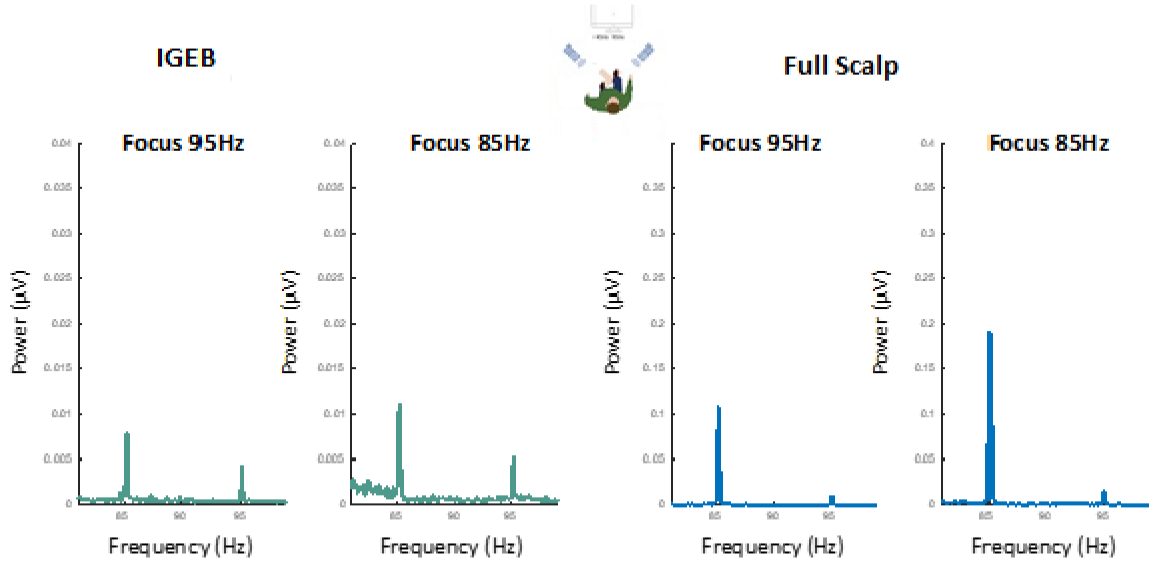
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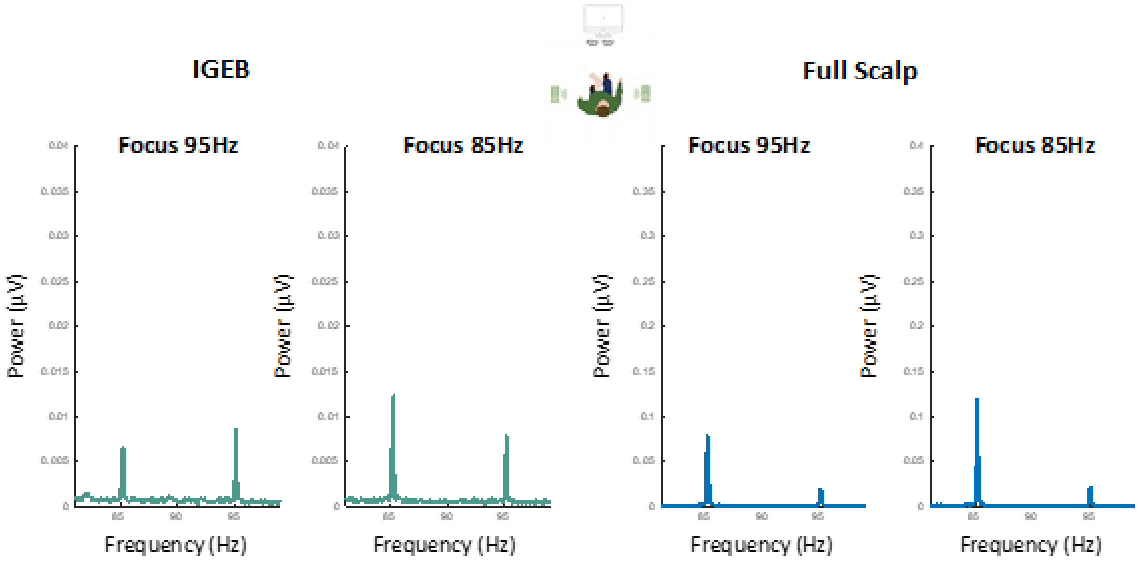

Figure 25: FFT of EEG responses to simultaneous 95Hz and 85Hz auditory stimulation across both attentional allocation conditions and four speaker locations. Left: in-ear EEG; Right: full-scalp EEG.

Similar to the results obtained in Experiment 2b, both EEG systems (full-scalp and in-ear) reveal peaks in the FFT at both stimulation frequencies (see Figure 23). No difference regarding attended vs. non-attended stimulation can be found. Across the speaker location conditions, only when speakers are located directly next to each other in front of the participant, did SNR values seem to drop slightly.Overall, responses to 85Hz stimulation (left side) seemed to elicit stronger neuronal responses.

4.2.4 Discussion

The experiments reported above aimed to generate fundamental knowledge in using the IDUN in-ear sensor system by focusing on “what can we do?” and “does it work?”. In the following, certain aspects derived from these experiments are explored in more detail and their implications for future research are addressed.

Validity of in-ear EEG and the ASSR

The presented EEG results confirm the IDUN Guardian’s ability to reliably measure neuronal processes of the auditory cortex. The comparison between in-ear and full-scalp EEG measurements revealed a lower SNR across all measurements when collecting ASSR from the ear canal. This was to be expected due to a smaller distance between the cortical source of activity and the more optimal alignment of electrodes to electrical dipoles when measuring from the scalp compared to the ear. Nonetheless, ASSRs were reliably picked-up by our in-ear EEG system at different stimulation frequencies (85 Hz, 90 Hz, 95 Hz), with different forms of presentation (headphones and speakers), and from different locations around the listener. Further, the ability of in-ear EEG to measure two concurrently presented auditory stimuli was demonstrated, even when presented from speakers placed very close to each other or behind the listener. The findings show the potential of EEG to measure the processing of multiple sounds from a person's environment. In Experiments 2b and 2c participants were instructed to focus on one of the two stimuli while trying to ignore the other one. The aim of this experimental manipulation was to investigate potential differences in ASSRs between attended and not-attended hearing. Unfortunately, in our experiments, it was not possible to distinguish those two conditions based on EEG responses. Previous research has shown that attention can modulate ASSR (for a summary of research on attentional modulation of ASSR, see (Mahajan et al., 2014)). However – without going into details – some inconsistencies between many of those studies raise the question of the robustness of this effect (e.g., concerning the optimal stimulation frequency range; contradicting effects from ipsilateral vs. contralateral stimulation). The current study suffered from potential limitations in that participants were not able to distinguish between both auditory stimuli and therefore could not focus on one while ignoring the other. In fact, 7 out of 12 participants reported not being able, or only with difficulty, to focus on one of the two sounds.

Nevertheless, we interpret the current in-ear EEG findings of experiment block 2 as the first proof of the IDUN Guardian's potential to decode auditory attention. ASSRs consist of neuronal oscillations entrained to the frequency and phase of an auditory stimulus presented at a certain repetition rate. Similarly, when we listen to human speech, neuronal activity in the auditory cortices is entrained by the rhythm of the sound. The main idea of auditory attention decoding (AAD) is to decode the (un-) attended speech envelope from the EEG signal by using a decoder. Recent research has focused on solving this challenge with new algorithms and has shown promising results (for a review, see, (Geirnaert et al., 2021)), even with ear-EEG (Fiedler et al., 2017; Nogueira et al., 2019).

Future advances in AAD algorithms together with mobile lightweight EEG solutions could lead to a new assistive solution for the hearing impaired (e.g., neuro-steered hearing devices).

Noise sources and their potential correlation to impedances

Here, underlying noise sources in the IDUN in-ear sensor were explored in more detail and whether these are in any way correlated to the impedance. For this, we extracted white and pink noise based on an EEG noise model proposed by Barry et al. (2021). Furthermore, we also investigated whether the signal quality as determined by EEG quality score (or EEG quality index) would be correlated to the impedance. The quality score followed ideas from Fickling et al. 2019, and it is computed based on multiple time- and frequency domain EEG metrics (Fickling et al., 2019); we have further adapted its usability to the IDUN in-ear sensor data. From the results, we did not find strong correlation (computed using Pearson correlation) of white (ρ = -0.09) or pink noise (ρ = 0.24) to the skin-contact impedance (Figure 36). Interestingly, we found a large positive correlation (ρ = 0.6) between the EEG quality score and the impedance which may imply that good impedance is related to good signal quality.

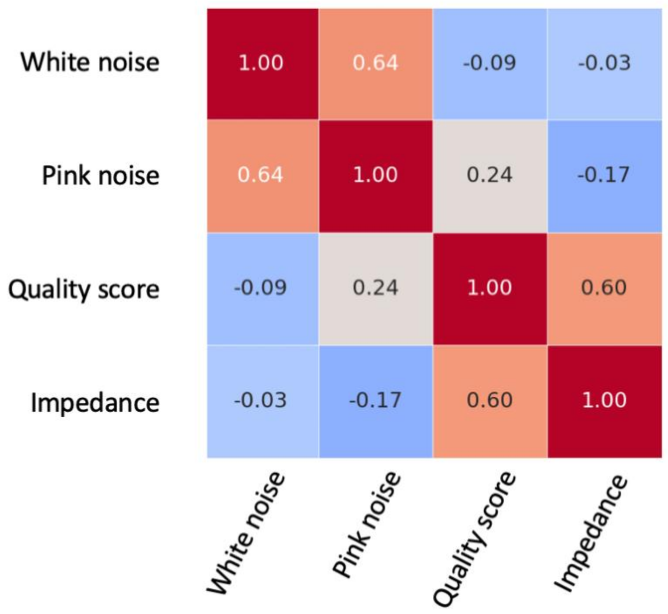

Figure 26: Pearson correlation between noise components and impedance. In addition, we also computed the correlation between impedance and quality score

5 Conclusion

In summary, the IDUN Guardian represents a significant step forward in bringing in-ear EEG into a form where it can be widely used in the consumer market. Firstly, it greatly improves comfort and usability for the user by using dry electrodes that require minimum effort for set up and use. Secondly, the IDUN Guardian earpieces are indistinguishable from regular consumer earbuds which are already socially accepted. This opens the door for longitudinal measuring of EEG signals over months and possibly even years, thus providing a goldmine of EEG data that can be used for different purposes. The experiments reported in this white paper show that the IDUN Guardian can robustly detect EEG markers characteristic for sleep onset and stage transitions in the sleep use case. In the hearing use case, the presented EEG results confirm the IDUN Guardian's ability to reliably measure neuronal processes of the auditory cortex. From the discussion, it is also clear that certain aspects of the hardware and software can be improved to increase the robustness of recording, reliability of sleep staging, and detection of auditory signals. Future versions of the IDUN Guardian will feature improved ergonomics, a smaller design, a mobile application and upgrades to the software capabilities including new classifiers to automatically label the EEG in real-time, a public API, and a TypeScript SDK to allow third parties to build neuro-enhanced products and services.

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