SPECIAL SECTION
BRAIN–MACHINE INTERFACE SYSTEMS

Neural Interface Instrumented Virtual Reality Headsets

Toward Next-Generation Immersive Applications

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The last decade has seen a strong resurgence of virtual reality (VR) and augmented reality (AR) applications, ranging from entertainment to neurorehabilitation. Users of VR headsets, however, often experience motion sickness symptoms, commonly referred to as *cybersickness*. For developers of immersive content, it is hard to measure in real time users' perceptions of immersion and the quality of experience (QoE) provided by the application. Commonly, subjective testing via questionnaires is used. Moreover, when applied in clinical applications, such as to treat phobias or in neurorehabilitation, it is hard to quantitatively gauge the success of different treatments other than through the use of subjective outcome measures.

To address these issues, we describe the development of a portable, wireless body/brain–machine interface that is integrated into an off-the-shelf VR head-mounted display (HMD). We describe the prototyping and validation steps of how to equip the HMD with off-the-shelf sensors and

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wireless amplifiers. In particular, the developed prototype integrates electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), and facial electromyogram (EMG) sensors directly into the HMD. We list potential applications for the instrumented HMD and hope that the work presented here will inspire researchers from diverse fields to reproduce and adapt the proposed prototype to instrument their own research and develop next-generation immersive applications.

QoE in VR and AR Applications

In the last decade, advances in computational power, computer graphics, and sensors have brought to the market a diverse array of consumer-grade HMDs for VR and AR applications. Representative examples include the Oculus Rift, HTC Vive, PlayStation VR, and Microsoft Hololens, to name a few. These devices have brought immersive applications to the general public. Moreover, the near future of VR/AR applications looks promising with the arrival of improved real-time tracking due to the use of cameras on HMDs and standalone HMDs, such as the Oculus Quest [1]. In addition to gaming applications aimed at the mass market, AR/VR applications are also burgeoning in areas such as rehabilitation [2], medical training [3], [4], education [5], work training [6], and the treatment of different disorders and phobias [7].

However, despite the advances seen in hardware and software, VR applications have still not reached credible simulation of a real experience [8]. First, the sense of immersion or presence has yet to achieve levels in which conscious awareness of a simulated environment disappears. Second, the bodily discomfort associated with exposure to VR content, or so-called cybersickness, can affect between 30% and 80% of users, with symptoms lasting for several hours [8]. Moreover, as emphasized in [9], "ultimately, the success or failure of any system for immersive communication lies in the quality of the human experience that it provides, not in the technology that it uses." QoE is a complex concept that is related to three groups of influential factors: technological, contextual, and human. Examples of human influential factors include stress, affective state, engagement, and attention, among others [10].

Measuring the human perception of immersion, presence, and/or experience as well as cybersickness has typically relied on subjective testing via (postexperience) questionnaires, such as the Virtual Reality Sickness Questionnaire [11], and the Presence and Immersive Tendencies questionnaires [12]. Subjective tests are expensive and time consuming, and they are performed after the immersive application is finished; therefore, they rely on the user's ability to recall events and aggregate them into an overall immersion/presence/experience rating. As such, subjective testing can be highly biased, lacks temporal resolution, and allows for only offline analyses.

As an alternative to subjective methods, recent research has made use of body–machine interfaces (BMIs) to characterize the user cognitive state through the analysis of physiological signals [13]–[15]. A special type of BMI is the passive brain–machine (or brain–computer) interface, which measures neurophysiological signals, usually EEG and/or near-infrared spectroscopy, and extracts correlates for different perceptual and cognitive processes [16]. Other BMIs have relied on modalities such as ECG, respiration, EOG, galvanic skin response (GSR), facial EMG, eye gaze, and pupillometry, to name a few [15]. BMIs have been used, for example, to measure stress [17], engagement [18], emotions [19], sense of presence [8], [20], immersion [21], experience [22], and cybersickness [8], [23]; thus, they can play a key role in advancing VR applications. Additionally, multimodal BMIs provide a better understanding of the cognitive process involved, because different physiological modalities exhibit complementary information [24].

Recently, VR applications have started emerging within health care [25], neurorehabilitation [26], and educational programs [5], to name a few domains. In such scenarios, it is hard to gauge the effectiveness of such interventions in an objective, quantitative manner, and subjective behavioral assessments or short-/long-term outcomes are typically monitored (e.g., [27], [28]). Within such scenarios, BMIs may also play a key role and could provide not only real-time feedback on, for example, student engagement [29] or stroke recovery [30], but also enable neurofeedback-based immersive applications [31].

In the past, modalities, such as heart rate (HR) and GSR, have been used to monitor the affective and stress levels of users in immersive environments [22]. Although other modalities, such as EEG, can provide more accurate measures of, for example, mental workload, the use of EEG presents many challenges, as an EEG cap needs to be worn (with dozens of electrodes) under the HMD. This can be time consuming and messy (if gel-based sensors are used), and it may cause interference with the collected EEG signals. The latter condition is exacerbated with wired EEG systems, as they require the user to remain seated to minimize movement artifacts; this can be extremely limiting for mobile immersive applications.

Notwithstanding, Neurable [46] has recently introduced a six-channel EEG headset integrated into an HMD for brain-controlled videogames. As the games rely on steady-state, visually evoked potentials (SSVEPs), the EEG channel locations are fixed, thus limiting the use of this device for applications outside the SSVEP domain. Moreover, only EEG sensors are integrated, thus further limiting the use of the device as a passive BMI to explore user cognitive processes. To address these issues, we describe the development of system that combines an open source, wireless, and multimodal BMI with an off-the-shelf HMD. The proposed system is capable of measuring EEG, EOG, ECG, and facial EMG in a portable, wireless, and noninvasive manner using only dry electrodes. The system was tested and validated under varying conditions. We conclude by showing representative examples of what the BMI–HMD could be used for across multiple fields.

BMI–HMD Development

The developed the BMI–HMD comprises three main parts: 1) a portable, wireless biopotential amplifier module to measure, record, and transmit the physiological signals; 2) an HMD-based VR/AR system; and 3) dry electrodes for the sensing of physiological potentials. With the aim of fostering reproducibility, off-the-shelf components were used, with minimal modifications needed. The following sections present these three parts in more detail.

Biopotential Amplifier Module

To enable practical mobile applications, the biopotential amplifier module must be suitable for acquiring different physiological modalities (portable, inexpensive, and light) as well as have wireless communication capability. Given these requirements, we selected the OpenBCI Cyton board (composed by eight fully differential; independently programmable; and high-gain, low-noise input channels), along with its optional daisy board, which provides eight extra input channels [47]. The analog front end in both boards is the TI ADS1299 analog-to-digital converter for biopotentials, which is designed for multiple modalities, such as ECG, EOG, EEG, and EMG. The OpenBCI hardware has been shown to be an acceptable alternative to traditional research EEG amplifiers [32].

Snap-ended cables [48] were used to support a great variety of standard electrodes. To power the OpenBCI boards, we used a 1,000-mA at 3.7-V lithium polymer battery; the capacity of the battery was calculated to last 12 h. Finally, the OpenBCI boards, the battery, and a USB charger [49] were placed in a custom-designed, 3D-printed case to host and protect the electronic components.

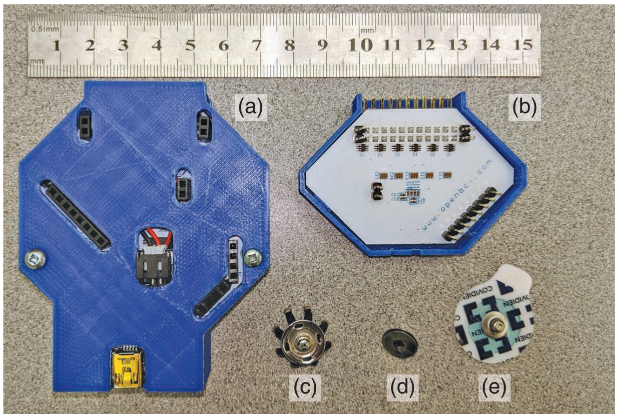

Figure 1. The biopotential amplifier module and electrodes: (a) the case for OpenBCI Cyton, battery, and charger; (b) the case for the daisy board; (c) a dry flexible electrode; (d) a dry flat electrode; and (e) a disposable electrode.

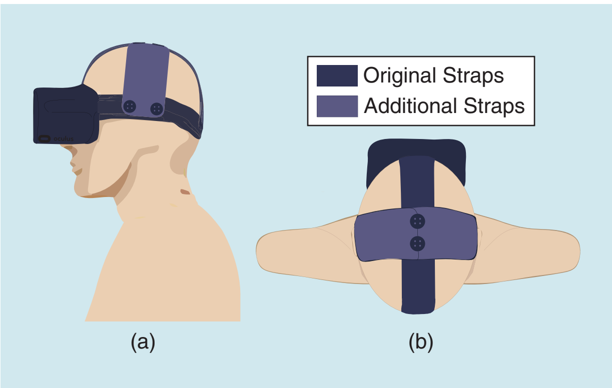

Figure 2. The HMD head-strap organization: (a) profile and (b) top views.

To keep the modularity aspect of the OpenBCI boards, the case was divided into two parts. One part encloses the OpenBCI Cyton board along with the battery and charger [Figure 1(a)]; thus, it can be used alone if only eight channels are required. In turn, the second part hosts the daisy board [Figure 1(b)]. The 3D model of the case has been made available online [50] to facilitate reproduction. Features of the OpenBCI biopotential amplifier include:

- a single amplifier for multiple physiological modalities: EEG, ECG, EOG, and EMG
- wireless communication using the OpenBCI USB dongle
- configurable to eight or 16 channels
- an ability to make each channel fully differential (bipolar), or single reference (monopolar)
- programmable gain for each channel
- light, at 86 g for the 16-channel configuration and 70 g for the eight-channel configuration
- 12 h of operation for 16-channel configuration.

Other amplifiers can also be used [51].

Off-the-Shelf HMD

An Oculus Rift (Development Kit 2) was used with the following specifications: frame rate of 75 Hz and a field of view (FOV) of 100°. Although the used HMD is not designed for AR applications, a similar approach to the one presented here can be performed in other HMDs, such as the HTC Vive. The original head straps of the HMD are ideal spots to place dry flexible electrodes, as they cover relevant brain regions over the scalp (e.g., central, parietal, temporal, and occipital). Additional textile straps were also added to allow for more brain regions to be monitored, such as in the case of cybersickness measurement. Figure 2 illustrates the original and additional strap positions. The HMD straps also serve as support to place the biopotential amplifier.

Dry Electrodes

The selection of the dry electrodes was based on three criteria: signal quality, practicality, and comfort [33]. Three different types of electrodes were used—flexible, flat, and sticker (disposable)—depending on their location in the HMD. Silver/silver chloride (Ag/AgCl) dry flexible electrodes [52] were used for EEG measurement in locations with the presence of hair. Flat Ag/AgCl dry electrodes [53] were implemented in places where contact with bare skin is needed and the electrode is physically supported by the HMD (i.e., around the face piece to record EOG, facial EMG, and frontal EEG). Finally, standard Ag/AgCl disposable sticker electrodes were used on bare skin where there was no support for the electrodes, such as at the mastoids (reference) and on the left collarbone (for ECG acquisition). The three types of electrodes are shown in Figure 1(c)–(e), respectively.

Hardware Integration

With the aim of using the 16-channel configuration to record EEG, EOG, ECG, and facial EMG signals, we proposed acquiring 11 EEG signals from electrodes located in three areas: frontal (Fp1, Fpz, and Fp2), central (FC1, FC2, Cz, CP1, and CP2), and occipital (O1, Oz, and O2). The EOG signals were derived from the EEG electrodes on the frontal area as well as two vertical and two horizontal electrodes placed on the face piece of the HMD. Facial EMG signals were also acquired from the electrodes on the face piece. Moreover, one electrode was placed on the user's collarbone with the goal of acquiring an ECG signal. Finally, the bias and the stimulus–reference–bias (SRB) terminals were placed on the mastoids. For this proposed 16-channel configuration, the placement of the electrodes can be seen in the layout depicted in Figure 3(a), and the face piece sensors are further shown in Figure 3(b). The layout can be easily modified depending on the experimental protocol. The final prototype can be seen in Figure 4. Plots of the 16 signals collected simultaneously are available as supplementary material.

Software Integration

The open-research philosophy behind the OpenBCI product line facilitates the integration of the developed system with myriad programming languages and communication protocols, including lab streaming layer, as well as open tools, such as OpenViBE, MNE, and our in-house-developed Multimedia/Multimodal Signal Analysis and Enhancement Lab EEG server (MuLES) [34].

Validation of the Developed BMI–HMD

To validate the developed BMI–HMD, four validation scenarios were proposed for each of the acquired modalities. A total of five participants wore the BMI–HMD under these scenarios. In our experiments, the VR applications were developed with Unity3D with synchronization using MuLES. The detailed instructions to replicate the validation scenarios are available online [54].

Validation of the EEG Signals

A common paradigm in EEG experimentation is the recording of SSVEPs, which are elicited in the visual cortex when a user gazes at a target that flickers at a specific frequency. The spectral content of the SSVEPs corresponds to the frequency of the flickering target. As such, the validation scenario for the EEG modality consisted of

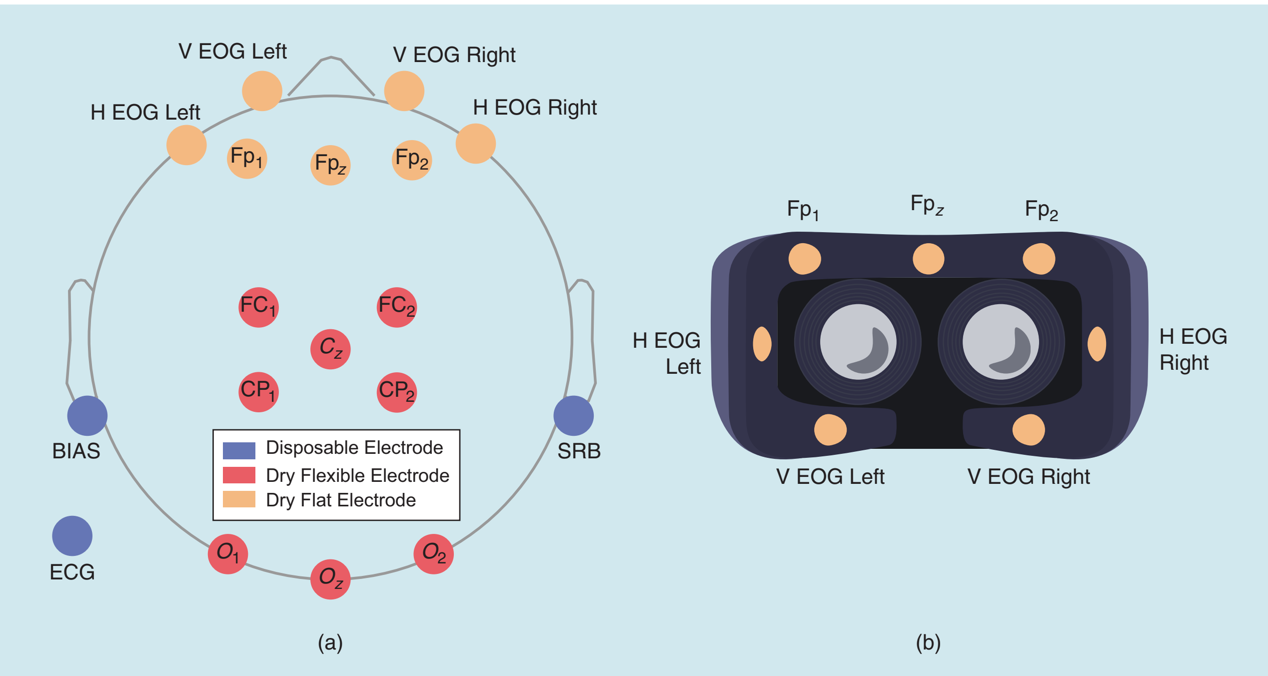

Figure 3. The proposed layout for the 16-channel configuration: (a) top view and (b) the electrodes on the face piece. H: horizontal; V: vertical.

three 30-s stages: 1) open eyes, 2) presentation of a blinking sphere at 12.5 Hz, and 3) closed eyes. The signal-to-noise ratio (SNR) was computed for the stimulus frequency (12.5 Hz) from the power spectrum as the ratio of the power at the stimulus frequency over the mean power of spectral components, 2 Hz over and under the stimulus frequency, for the three electrodes located in positions O1, Oz, and O2 [13]. Figure 5 presents the distributions of the average SNR values for each of the three stages. As expected, the SNR for the SSVEP is higher than for the other two conditions, thus validating the EEG modality.

Validation of the ECG Signal

In our experiments, the ECG electrode was placed on the left collarbone (see Figure 4). Although this location differs from standard ECG leads, it was shown to provide accurate R peaks, thus allowing us to calculate HR and HR variability (HRV). Such metrics have been used often to measure different mental states, particularly in VR [35]. To validate the accurate registration of the R peaks, a research-grade ECG monitor (Zephyr Bioharness3 chest band) was used alongside the developed BMI–HMD, and both ECG signals were simultaneously acquired for 10 min. Figure 6 depicts an 8-s segment of the ECG obtained via the collarbone sensors and the reference ECG signal. As can be seen, highly accurate cardiac measurement can be achieved, and the correlation between the instantaneous HR derived from both sensors was 0.996, thus validating the ECG modality.

Figure 4. The final BMI–HMD system encompassing 16 multimodality sensors and a wireless amplifier module attached to the top of the HMD straps.

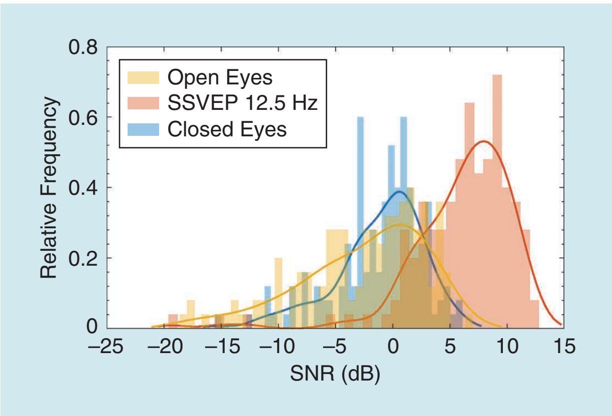

Figure 5. The distributions of the combined SNR values for the O1, Oz, and O2 electrodes for the eyes-open (yellow), eyes-closed (blue), and SSVEP (red) stages.

Validation of the EOG Signals

In this validation scenario, we used the acquired signals from the seven flat electrodes placed in the face plate of the HMD, as depicted in Figure 3(b). Here, we were interested in identifying the direction of the eye movements and blinks. Eye blinks have been shown to be useful in predicting cybersickness [23], whereas eye gaze detection could be particularly useful for foveated applications and gaze-adaptive content [36]. For this validation, users were asked to follow a target in the virtual environment for 5 min. The target moved from the center of the FOV to one of eight positions: right, right-up, up, left-up, left, left-down, down, and right-down; each position was repeated 12 times.

Figure 7 depicts the average response over the 12 trials for each of the seven electrodes, for each of the eight eye gaze positions as well as the average of a series of eye blinks. As can be seen in Figure 7(b), the acquired waveforms present different patterns depending on the

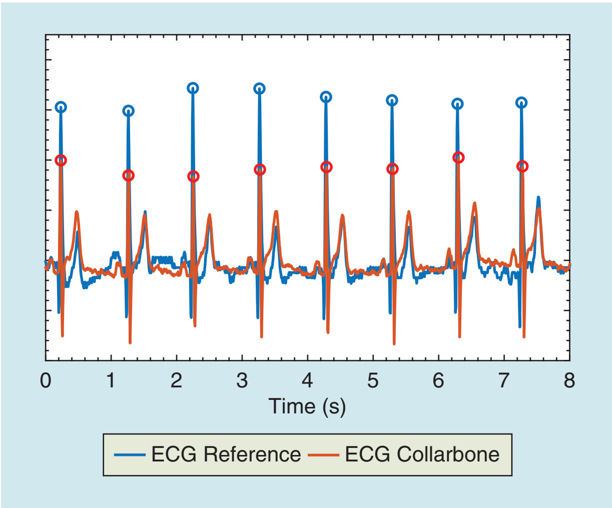

Figure 6. The ECG signals for the reference (blue) and prototype (red) devices. The locations of detected R peaks are indicated by circles. The *y*-axis units are arbitrary.

performed eye movement. For example, for the up and down directions, the horizontal EOG channels do not present changes, while the vertical EOG channels have opposite signs in those conditions. Similarly, a waveform sign change is observed in horizontal EOG channels for the left and right directions. In general, the acquired EOG waveforms follow the patterns reported in the literature [37], thus validating the EOG modalities.

Validation of the EMG Signals

Facial EMG signals can be used to detect different facial expressions. Although camera-based systems have often been used for this purpose, this becomes impossible when an HMD is blocking the face. Facial expressions can not only provide information about different mental states but also be used to control remote avatars in embodied virtual applications. For this validation scenario, signals from the seven face-piece electrodes were used. Users were presented with one of four cues indicating which facial expression to perform: neutral, angry, surprised, and happy. In this experiment, each expression was repeated 12 times over 5 min. For this analysis, the seven electrodes were re-referenced to Fpz and grouped into three categories: vertical (V EOG left and right), horizontal (H EOG left

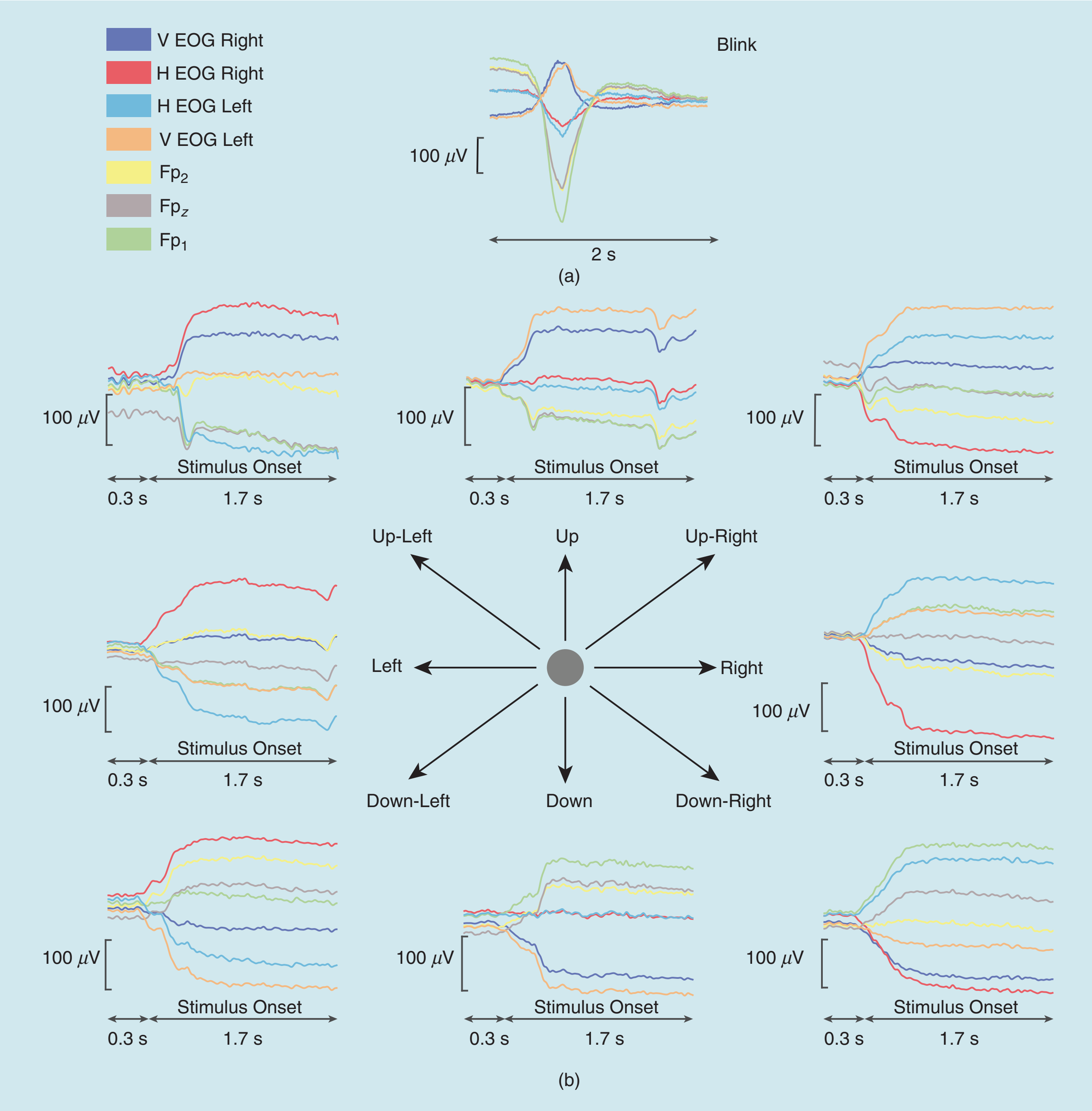

Figure 7. The average response for each electrode in the face piece of the HMD for (a) blinks and (b) saccades in different directions.

and right), and frontal (Fp1 and Fp2). Figure 8 presents the average response in each of the three electrode groups for each of the four facial gestures. As can be seen, varying facial expressions evoke different EMG activity over the electrode groups; thus, EMG signals can be used to classify facial gestures, as shown in [38].

Discussion and Next Steps

The proposed BMI–HMD has been built and validated to show accurate acquisition of EEG, HR and HVR, blinking, (coarse) eye-gaze tracking, and facial EMG for facial expression classification. Additional modalities may be inferred from these existing ones to further augment the capability of the prototype. One modality is breathing rate, which can be extracted from ECG modulations [39]. Breathing has been shown to be an important modality for controlling cybersickness symptoms [40] and could play an important role in adaptive serious games. With the simultaneous acquisition of multiple physiological signals, the next steps will involve their use not only in measuring the user's perception of immersion, presence, and/or engagement in real time but also to continuously adapt content to maximize the user's experience.

Moreover, as mentioned previously, cybersickness is currently a major limiting factor in the wide deployment and acceptance of VR applications. The developed BMI–HMD system is well poised to enable an objective characterization and, perhaps, even prediction of cybersickness. The combination of eye-gaze, HRV, EEG, and blink information may provide important cues for real-time cybersickness detection and allow immersive applications to adapt accordingly to avoid it, such as by placing static objects in the FOV or suggesting breathing exercises to reduce symptoms during immersion.

Visual fatigue is also another factor commonly observed in VR applications [41]. With the measured EOGs and occipital EEGs, immersive applications can be enabled that monitor the user's visual fatigue and adjust the content (e.g., lighting, color palette) accordingly. Moreover, being able to detect facial expressions while wearing an HMD can have applications not only in emotion detection but also in pain or fear evaluation in clinical applications that explore VR for phobia treatments [7].

Within educational, clinical, and neurorehabilitation applications, the developed BMI–HMD system can be used to monitor, for example, user engagement, attention, brain connectivity, emotional regulation, and pain. These can provide educators and clinicians with objective measures of treatment outcomes, thus more accurately characterizing the success of different treatments. Moreover, the developed BMI–HMD system may also open doors for a new modality of biofeedback, namely, virtual biofeedback. Such methods have been shown to be effective in treating specific psychiatric disorders, such as anxiety, autism, depression, schizophrenia, and posttraumatic stress disorder [42]. With a portable device that can provide virtual environments that closely resemble realistic ones, it is expected that improved results may be obtained [43]. Within the gaming realm, in turn, having direct access to attention, engagement, and stress measures can allow games to adjust based on the user, thus maximizing the game's fun factor [44].

The potential applications for the developed BMI–HMD are endless. We hope that, by using open-source hardware

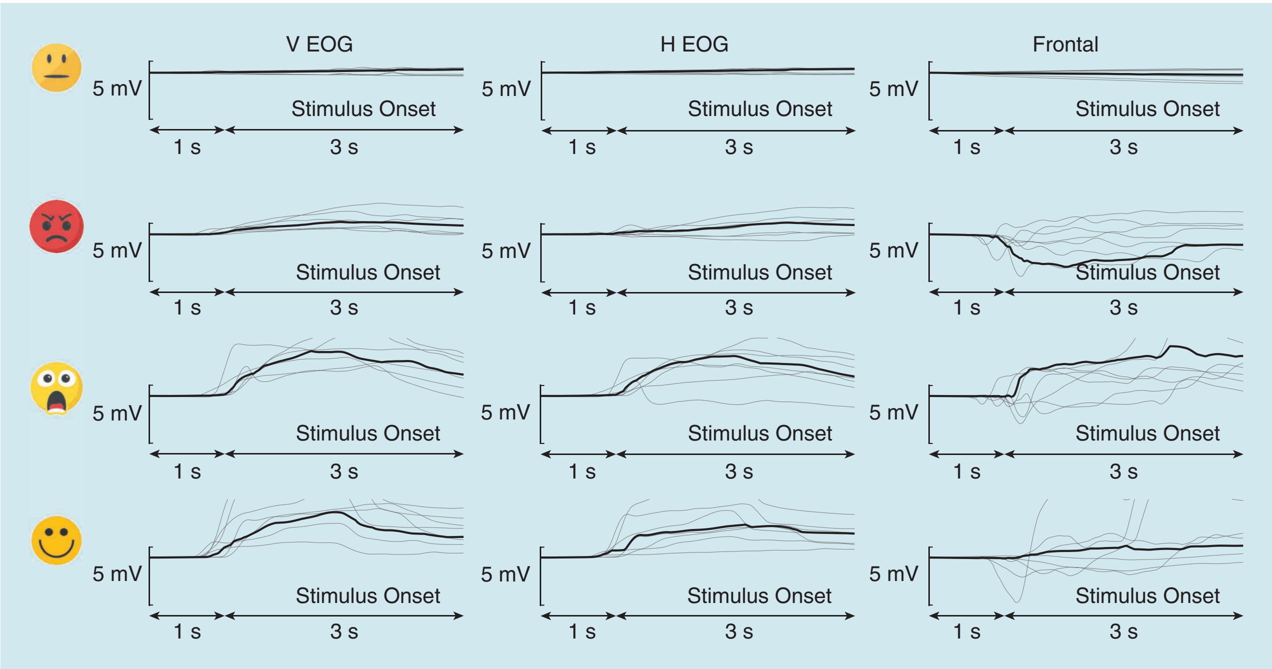

Figure 8. The average response for each facial-EMG group of electrodes for different facial expressions.

and software and providing all of the necessary scripts to run different tests, along with the details of how to put together the system, the work herein presented results useful for researchers across many different fields Similar to all other mobile EEG applications, signal processing steps are still needed to compensate for power-line interference and muscle and movement artifacts. The latter can be particularly troublesome in ambulant settings, but open-source algorithms [55] are available to enable accurate EEG analysis under such conditions [45].

Conclusion

In this article, we described the development and evaluation of a wireless, integrated BMI–HMD that allows for the acquisition of multimodal physiological signals, such as EEG, ECG, EOG, and facial EMG during mobile VR/AR applications. The developed system allows real-time feedback, measurement of relevant experience factors (e.g., sense of presence, cybersickness, and attention, among others), and the creation of objective outcome measures for different VR-based treatments. Future steps and numerous potential applications for the developed BMI–HMD were described and discussed.

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