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Wearable brain-computer interfaces and their applications: advancements from the ARHeMlab research group

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ABSTRACT: This work presents recent advancements in the development of wearable brain–computer interfaces (BCIs) by the ARHeMlab research group, focusing on the period from 2021 to 2025. The activities address the key challenges of translating BCIs from controlled laboratory settings to real-world, daily-life scenarios. The research integrates wearable and portable EEG hardware with custom signal processing pipelines and XR environments to enhance signal quality and user engagement. Experimental contributions span reactive, passive, and active BCI paradigms, including SSVEP-based interfaces with adaptive XR stimulation, cognitive load and distraction monitoring using low-channel EEG, and motor imagery control with multimodal neurofeedback. The proposed solutions are validated through application-specific studies, supporting the feasibility of practical, scalable, and ecologically valid BCI systems. No original research is presented in this work but the abovementioned works are reviewed.

INTRODUCTION

Brain–Computer Interfaces (BCIs) offer the potential to establish a direct communication pathway between the brain and external devices, thus disclosing novel applications in neurorehabilitation, assistive technologies, mental workload monitoring, and user engagement enhancement [1]. By interpreting neural signals, which are typically acquired through electroencephalography (EEG), BCIs can translate user intent into actionable outputs, offering an alternative control strategy for individuals with severe motor impairments and enriching human–machine interaction [2], [3].
Despite their promises, most BCI systems are often restricted to controlled laboratory environments due to cumbersome equipment, time-consuming setup procedures, and limited wearability [4]. These constraints significantly hinder the adoption of BCIs in everyday life and long-term use cases, such as home-based (neuro)rehabilitation, adaptive gaming, and continuous mental state monitoring. To bridge this gap, there is a growing demand for wearable BCI solutions, capable of delivering reliable performance while prioritizing user comfort, ease of use, and real-time operation [5], [6].

Recent literature highlights an increase in the development of compact, low-density EEG systems, dry-sensor technologies, and wireless platforms integrated with extended reality (XR) [7], [8]. These advances are complemented by machine learning techniques for robust signal classification, as well as multimodal feedback strategies to enhance user engagement and signal quality [9, 10]. At the same time, challenges such as reduced signal-to-noise ratio, calibration time, artifact susceptibility, and inter-user variability remain open areas of investigation, particularly for mobile and self-paced BCI systems [11, 12].

Within this framework, the Augmented Reality for Health Monitoring laboratory (ARHeMlab) research group contributes to the advancement of wearable BCIs, focusing on the metrological validation of consumer-grade components for BCI, the development of neurofeedback protocols based on dry sensor technology, and the integration of BCIs into immersive and adaptive environments. For instance, previous works involved engagement monitoring in educational and rehabilitative settings, rehabilitation protocols with multimodal sensory feedback, and real-time interaction. Emphasis is placed on uncertainty-aware signal acquisition, signal processing pipelines tailored to low-channel systems, and user-centred experimental design.

This paper thus gives an overview of the key advancements from the ARHeMlab group in contributing to the progression of wearable BCI research by tackling three

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core aspects: (i) signal acquisition through wearable and portable EEG setups, (ii) processing strategies suitable for low-channel setting and possibly real-time classification, (iii) sensory stimulation and/or feedback designed for natural and engaging user interaction. Findings are supported by experimental validation and application-specific insights, illustrating a cohesive trajectory toward daily-life BCI deployment. It is worth remarking that only research from the ARHeMlab research group have been reviewed, by particularly contextualizing the findings in the field of wearable BCI systems.

WEARABLE BCI ARCHITECTURES

This section concerns the approaches to building wearable BCI systems by adopting consumer grade EEG hardware, developing processing pipeline tailored to few acquisition channels, and providing sensory stimulation and/or feedback mainly through XR. The reference architecture is reported in Fig. 1 for the sake of clarity.

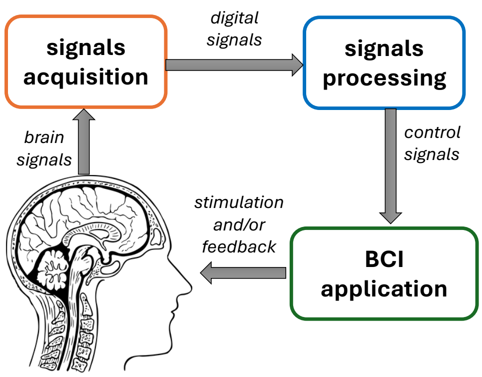

Figure 1: Essential block diagram of a wearable brain-computer interface.

Signal acquisition: To ensure usability in real-world contexts, the signal acquisition strategy for the developed BCI systems emphasizes practical wearability without compromising essential signal quality. Proposed architectures involve three main pillars: a reduced number of channels, the use of suitable commercial devices, and a strong focus on metrological aspects to address performance limitations.

In contrast to traditional EEG systems that rely on high-density montages, proposed designs prioritize a low number of electrodes (typically 1 to 8), enabling faster setup times, reduced discomfort, and enhanced mobility [13–15]. Electrode placement is task-specific: occipital positions are preferred for Steady-State Visually Evoked Potentials (SSVEPs), sensorimotor areas are targeted for Motor Imagery (MI)-based applications, while the frontal area is privileged for cognitive load assessment [16]. Despite the inherent trade-off in spatial resolution, the studies have demonstrated that minimal setups can still bring to meaningful classification accuracy in various contexts, including XR-enhanced interaction, motor rehabilitation, and engagement monitoring [13, 15, 17–19]. This is partly due to the temporal resolution, where sampling rates of the chosen devices span from 125 Sa/s to 1024 Sa/s.

To promote scalability and lower costs, commercial-grade wireless EEG systems were adopted. The chosen instrumentation often features dry electrodes. Acquisition devices, selected also for their ergonomic design, were EEG-SMT by Olimex, Helmate by abmedica, Emotiv Epoch, FlexEEG by Neuroconcise, and Unicorn Hybrid Black by g.tec. Safety standards and real-time data acquisition capabilities were also taken into account. These systems facilitate the BCI usage even where user movement and portability are foreseen [15], and apart from the Helmate case, they support integration with wearable XR interfaces [18, 20].

Recognizing the limitations introduced by wearable EEG systems, metrological characterizations were conducted for the selected equipment. Evaluated performances were related to acquisition latencies, sampling stability, linearity errors, and amplitude uncertainties [20, 21]. Particular attention was paid to the impact of wireless communication and electrode-skin interface, both of which can affect the detection of time-locked phenomena and real-time usage.

The discussed approach to signal acquisition aims to the identification of bottlenecks to performance while enabling wearable and user-friendly solutions for continuous daily-life applications. By tackling the mentioned aspects, disclosed out-of-the-lab scenarios. Nonetheless, optimizing signal-to-noise ratio also requires channel selection and artifact removal by involving tailored signal processing pipelines, which are ultimately devoted to a proper classification of the acquired brain signals.

Signal processing:

Artifacts removal is a fundamental step to detect neural activity inside the signals acquired via wearable and portable systems. Given the adoption of low-density EEG setups, well-known techniques like Independent Component Analysis, Principal Component Analysis, and Artifact Subspace Reconstruction (ASR), were firstly investigated. ASR demonstrated superior performance in preserving EEG integrity when at least four electrodes were available [22]. Instead, for conditions involving fewer sensors, a hybrid technique integrating ASR with multivariate empirical mode decomposition was developed to deal with ocular, blink, and muscular artifacts [23]. Currently, techniques relying on Riemannian geometry are also under investigation.

In reduced EEG channels sets, carefully choosing the ones to install is also crucial to optimize the available brain signals information. As anticipated above, electrodes placement can be done with a-priori knowledge on brain areas. Nonetheless, data-driven selection was investigated as well [13]. Sequential feature selection approaches were implemented in conjunction with different classifiers (k-NN, SVM, LDA, RF, and ANN), and a leave-one-subject-out cross-validation scheme was

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adopted to choose subject-independent channels [24]. While previous works had already supported the placement around sensorimotor area for MI, electrodes in the frontal and parietal areas consistently emerged as the most informative for cognitive load-related EEG analysis in more recent studies. Such evidences are in accordance with multiple studies found in literature [10, 13].

Multiple classical machine learning algorithms were adopted for feature selection and classification. In active and passive paradigms, feature extraction was largely conducted using by Filter Bank Common Spatial Pattern, which applies Chebyshev band-pass filters followed by spatial projection to maximize inter-class variance [19, 25]. The selected features were classified through SVM, LDA, or Naive Bayesian Parzen Window, by considering computational constraints especially in real-time operation [26]. On the other side, studies for reactive BCI demonstrated that even simple classifiers like k-NN can outperform canonical methods such as Canonical Correlation Analysis (CCA) when optimized feature sets are used, providing a compelling case for ML in low-complexity wearable systems [18, 27].

Within the passive paradigm, the Sequential Feature Selection (SFS) algorithm was employed to identify optimised subsets of EEG features in the feature selection stage. SFS is a wrapper-based method that, given a target classifier, iteratively selects the most informative features, maximizing the classifier's performance by adding them one at a time (*forward selection*). SFS helps reduce overfitting and enhances model generalisation by tailoring feature selection to the specific classifier architecture [24].

In parallel to classical ML, deep learning models were evaluated for their capability to automatically learn feature representations. These architectures were particularly effective in scenarios involving emotion classification or mental state detection, leveraging both spatial and spectral information in an end-to-end fashion [28]. When embedded in real-time pipelines, simplified versions of FBCSP with minimal filter sets are sought to be combined with deep neural classifiers to achieve real-time BCI control [26]. Finally, Convolutional Variational Autoencoder were also investigated to boost artifacts removal [29].

Given the high inter-subject variability of EEG signals, domain adaptation (DA) and transfer learning methods are crucial for achieving generalizable models. Feature-based DA techniques such as Subspace Alignment and Transfer Component Analysis were investigated to align source and target data distributions prior to classification [30]. In the deep learning context, Domain-Adversarial Neural Networks (DANN) were employed to jointly optimize class separation and domain invariance. The use of unsupervised DA—leveraging unlabeled target data during training—proved particularly suitable for wearable BCIs, where session calibration time is often limited. Comparative ablation studies confirmed the performance gains offered by DA, with certain normalization strategies (e.g., Stratified Normalization) in some cases outperforming traditional DA methods alone.

Stimulation and feedback:

XR has been increasingly integrated to enhance both sensory stimulation and sensory feedback in BCI applications. This technology is devoted to creating realistic and adaptive environments that foster user engagement and facilitate neuroplasticity.

XR devices such as the Epson Moverio BT-350, Oculus Rift S, and Microsoft HoloLens 1 were employed to deliver targeted visual stimulation in reactive paradigms [18, 31]. Each device offers different capabilities in terms of field of view, refresh rate, and see-through technology. For instance, the Moverio and HoloLens are optical see-through devices, while the Oculus Rift S was adapted into a video see-through system. These headsets enabled the presentation of flickering visual stimuli for SSVEP elicitation at specific frequencies (e.g., 8–15 Hz), implemented using Unity3D.

In terms of feedback, XR systems delivered multimodal neurofeedback by combining visual and haptic modalities. Visual feedback was typically rendered as the motion of a virtual object (e.g., a bar, a ball or game avatar) within a Unity-based virtual environment [15, 25, 26]. The object's behaviour—such as direction and velocity—was dynamically modulated based on real-time EEG classification outputs, where the predicted class dictated movement direction and the classification confidence influenced intensity or speed. For haptic feedback, wearable vibrotactile technology like the bHaptics TactSuit X40 was employed. Vibrations were mapped to the user's torso based on the classified EEG signals, with direction and intensity corresponding to BCI output [15, 25].

XR feedback was also integrated into adaptive gaming environments, where BCI control allowed users to navigate avatars through virtual tasks such as collecting coins [26]. These scenarios included progressively challenging levels with changing environmental conditions (mainly increased speed). Feedback was tightly coupled with performance metrics such as score and time, offering real-time adjustments to maintain an engaging but manageable difficulty level.

APPLICATIONS AND ACHIEVEMENTS

This section reports the results achieved with the described architectures. These are grouped by adopted paradigm. The Institutions' Ethical Review Boards approved all experimental procedures involving human subjects for the respective works recalled in the following.

Reactive paradigms:

In the development of reactive BCIs, recent research activities in ARHeMLab have focused on SSVEP signals, with particular emphasis on the generation of visual stimuli through XR technology as an alternative to traditional computer screen (CS)-based setups. In fact, the recent advancements in XR technology, particularly in terms of pixel resolution and field of view (FoV), have made

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XR head-mounted displays (HMDs) a viable alternative for presenting visual stimuli, thereby enhancing system portability and immersivity and extending the applicability of SSVEP-based BCIs beyond controlled laboratory settings [14].

However, the use of XR-based systems introduces several challenges that can impair accurate target detection. Firstly, visual stimuli rendered in XR typically exhibit a degree of transparency to allow for superimposition onto the physical environment. This leads to a reduced contrast compared to CS setups, where the background is generally black and the stimuli are fully opaque. The consequent decrease in the signal-to-noise ratio (SNR) significantly affects system performance, particularly under ambient illumination levels exceeding 600 lux [32]. Another major issue relates to the hardware limitations inherent to XR HMDs, which often suffer from frame rate instability relative to their nominal specifications [18, 33]. Such fluctuations can lead to undesired shifts in the frequency of the flickering stimuli, thereby reducing the accuracy of target classification. As shown in Fig. 2, given an XR device with a nominal refresh rate of 30 Hz and programmed to generate visual stimulation at 15 Hz, a frame rate error resulting in 32 frames per second (fps) produces an SSVEP frequency of 16 Hz, thus compromising the system's reliability. Therefore, measuring frame rate stability is essential and requires careful optimization of the software used to deliver the stimuli.

To address these limitations, several mitigation strategies have been developed. In [18], a classification algorithm capable of adapting to the actual frame rate of the AR device was proposed, leading to significant performance improvements over an otherwise identical XR-based system lacking this self-adaptive capability. Furthermore, in [27], the use of machine learning-based classifiers was investigated as an alternative to conventional techniques such as CCA. The results demonstrated clear enhancements in classification accuracy through the application of machine learning methods.

Overall, the incorporation of frame rate error awareness into stimulus generation, coupled with the implementation of self-adaptive classification algorithms, including those based on Machine Learning, has enabled the development of highly wearable XR-based SSVEP BCIs. These systems can operate with a reduced number of EEG channels, including single-channel configurations, while achieving performance levels comparable to state-of-the-art CS-based systems.

Passive paradigms:

Within the context of BCIs, passive paradigms enable continuous monitoring of users' cognitive states without requiring an intentional interaction. These paradigms rely on EEG signals to detect conditions such as fatigue, stress, or distraction, and offer promising applications in both clinical and operational domains. In this perspective, the study in [24] investigated cognitive load in neurosurgeons engaged in fine motor tasks. Six trainee neurosurgeons were monitored using an eight-channel EEG

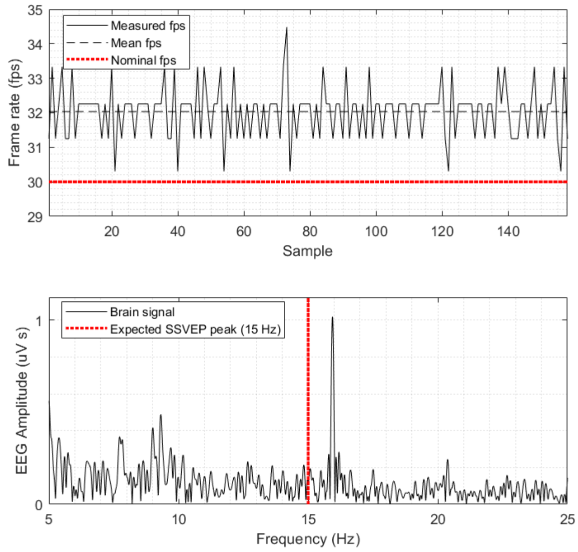

Figure 2: Example of fps variation in an XR HMD used to generate SSVEP stimuli.

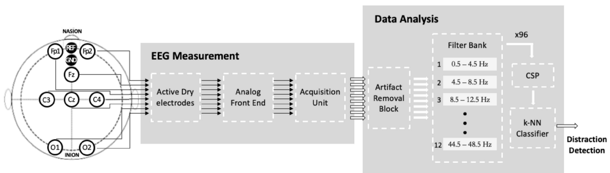

Figure 3: The proposed distraction-detection method (CSP: Common Spatial Pattern algorithm).

system while performing the Purdue Pegboard Test at two difficulty levels. EEG analysis, supported by SFS and supervised classifiers, identified relative alpha power in Fz, O1, and O2 as key markers of mental workload, achieving up to 100 % accuracy in detecting cognitive load levels. The employed lightweight, wireless system allows for real-time monitoring of cognitive fatigue, a common condition in neurosurgical practice.

In [34], a wearable EEG device-based method for detecting distraction during motor rehabilitation exercises was proposed (Fig. 3). An average classification accuracy of 92.8 % in distinguishing attentive from distracted states was achieved by combining a 12-band filter bank with the Common Spatial Pattern (CSP) algorithm. The EEG device's high wearability makes it suitable for clinical implementation, providing therapists with real-time information to manage and enhance patient engagement.

Both studies demonstrate how passive BCIs, implemented through wearable EEG technologies, can monitor cognitive states during motor activity. While the former focuses on preventing mental overload in high-stakes surgical settings, the latter addresses patient engagement in rehabilitation contexts. These contributions underscore the potential of passive paradigms to support adaptive interventions across several real-world healthcare environments.

Active paradigms:

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In exploring wearable BCIs based on motor imagery for daily-life contexts, initial efforts focused on evaluating signal processing and classification strategies for motor imagery detection as they were proposed and validated in scientific literature. Both knowledge-based and deep learning approaches demonstrated comparable performance in the 83 % to 93 % range. Despite requiring feature engineering, traditional methods like CSP combined with LASSO and SVM offered low-latency and efficient solutions especially for binary classification. In contrast, deep learning strategies provided superior performance in multi-class problems by directly learning representations from raw EEG data. Despite the results, data augmentation and transfer learning are under exploration to mitigate data scarcity and improve model generalization.

Building upon this, the next phase involved incorporating neurofeedback to enhance user engagement and measurand quality. A wearable closed-loop BCI was developed using wet and then dry EEG sensors, as well as a vibrotactile chest-based feedback system. Visual, haptic, and combined feedback modalities were tested under a synchronous paradigm. Notably, multimodal feedback tended to improve classification accuracy by 5–12 % with respect to the absence of feedback (statistical significance confirmed by permutation test with $\alpha = 5\,\%$). Moreover, dry sensors facilitated usage but introduced artifacts, particularly in long-haired users or when vibration was activated for the haptic feedback. Still, user feedback via system usability and user experience questionnaires indicated overall system usability and comfort, despite increased perceived effort (NASA-TLX) in the neurofeedback group.

To enhance natural interaction and reduce dependence on external triggers, the study progressed to implementing a self-paced BCI framework. A gamified virtual reality environment allowed participants to control an avatar using continuous MI commands without explicit cues. Among 23 participants, a 54 % ± 15 % composite classification accuracy (3 balanced classes) was achieved during system calibration. Yet, most user were able to properly control the avatar through reaching the targets as reconstructed in Fig. 4. Future work will target reducing calibration time and improving feature separability through refined models and transfer learning approaches, so as to keep developing scalable and practical BCI applications for real-world scenarios.

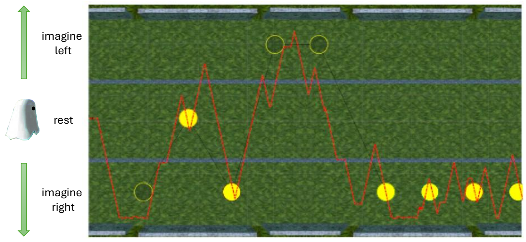

Figure 4: Reconstructed path (red line) of the ghost avatar controlled by a wearable active BCI. Collected targets are in yellow, missed ones in gray.

CONCLUSIONS

This contribution described ARHeMlab's research activities from 2021 to 2025 focusing on the deployment of BCI systems suitable for use outside the laboratory. By integrating wearable and portable EEG with multimodal XR-based feedback and machine learning-enhanced signal processing, the group addressed major limitations in wearability, usability, and robustness. The results validate the feasibility of real-time, low-channel BCI implementations across reactive, passive, and active paradigms. Future work will focus on reducing calibration times, improving cross-subject generalization through transfer learning, and optimizing signal acquisition under unconstrained conditions, paving the way for widespread application in healthcare, entertainment, and industrial sectors.

Further recent technologies are currently under exploration by the ARHeMlab group working on the wearable BCI domain. These include novel XR visors (e.g., Hololens 2 and Meta Quest 3) with the addition of vibrotactile feedback, as well as advanced signal processing techniques, such as task-related component analysis, filter-bank CCA, data augmentation, and adversarial neural networks. On the other hand, the inter-subject and intra-subject performance will need deeper investigations by extending the reviewed results to different sensory feedbacks and by greater sample sizes.

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