Brainwear: Towards Multi-modal Garment Integrated EEG

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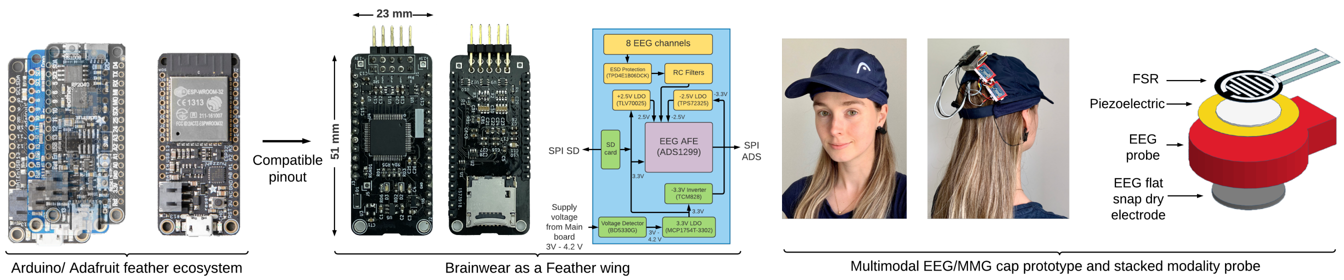

Figure 1: Left: Brainwear is compatible with the Adafruit Feather footprint. Right: aesthetical wearable for HAR and multi-modal probe.

ABSTRACT

We aim to facilitate broad use of EEG sensing in multi-modal smart garments by developing an open-source EEG sensing module with the state-of-the-art analog front-end that is pin/protocol-compatible with popular ecosystems in the wearable and DIY community. The EEG functionality is validated with the neuroscience standard n-back memory load task. We also demonstrate the seamless integration of EEG electrodes with low-frequency Force Sensitive Resistors (FSR) and high-frequency piezoelectric sensors within a single probe. Finally, we show the embedding of the entire setup in a textile baseball cap. We also present how signals from the different modalities complement each other under situations such as motion artifacts and different activities from an unobtrusive head-worn garment. The system is available to the community through a public GitHub repository.

CCS CONCEPTS

• **Computer systems organization → Embedded systems**.

KEYWORDS

Wearable EEG; Brain-Computer-Interface; Open-source toolkit

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1 INTRODUCTION

Sensing brain activity, including (but not limited to) Brain-Computer Interfaces (BCI), is increasingly becoming an active research topic in wearable computing. There are several initial consumer-grade applications as explored in [23]. Most work on brain activity monitoring uses non-invasive EEG for its high temporal resolution, low cost, and portability capabilities. [30]. However, most current commercial wearable EEG devices have not gained high adoption due to issues like comfort and social acceptance, especially for long-term use. Most EEG work is constrained to laboratory environments in which the user's movement is restricted due to high sensitivity and motion artifacts, thus limiting the research questions that such studies can address [23]. Hence, research and future consumer applications towards the "Transparent EEG" concept[4] require long-term solutions that are at the same time aesthetically appealing, easy-to-use, motion/noise-tolerant. For the latter, in particular, close integration with additional sensors is a promising approach. Finally, broadly accessible platforms that can be easily used and extended by the community are needed [20]. While addressing such usability and multi-modal issues is the forte of the collective wearable community, the current barrier encapsulating EEG technologies has so far discouraged highly needed advancements.

In our summary of neuroscience studies regarding human activity recognition (HAR) in Section 2, EEG proves to be a potent sensing modality. Yet, the adaptation of EEG in wearable HAR studies has so far been limited due to the reasons explained above. Thus, we developed an open-source EEG module that is hardware compatible with the popular Adafruit Feather family based on the Arduino ecosystem. We have also demonstrated how EEG electrodes can be seamlessly stack-integrated with FSR and piezoelectric sensors within a single probe. This design initiative aims to bring the EEG modality more accessible to the wearable computing community to promote future studies with EEG-integrated garments combining other sensing modalities.

To bridge the gap between wearable BCI and HAR, **our contributions are**:

(1) We developed a compact, easy-to-use Arduino-based EEG module, Brainwear, which we provide as a complete open-source toolkit to the community[1].
(2) We implemented a proof of concept application of the system in a normal baseball cap.
(3) The EEG performance in the cap prototype was evaluated on a standard neuroscience benchmark (n-back).
(4) We showed that additional sensing modalities, specifically FSR (pressure sensing) and piezoelectric, can be integrated within each single sensor probe in the cap.
(5) On a set of example signals, we demonstrate and discuss the benefit of combining EEG with the additional sensors in a single device.

2 BACKGROUND AND STATE OF THE ART

In the **wearable HAR** discipline, EEG has already shown great potential [29]. As summarized in Table 1, EEG can provide information on many psychological and cognitive aspects where physiological sensors usually struggle. However, none of these studies has seamlessly integrated EEG with other physiological modalities in a single embedded system - the EEG signal is always provided by specialized hardware with obvious barriers of garment integration.

Ad hoc EEG systems or components have been created in various studies. For example, [7] developed novel 3D-printed electrodes that are located into an e-Textile headband. [20] combined the around-the-ear electrodes (cEEGrigs) proposed by [4] and the OpenBCI platform to create a ready-to-wear device to recognize mental workload as well as other BCI tasks.

Recent **commercial mobile EEG devices**, such as Mindwave (Neurosky), Muse (InteraXon), and EPOC (Emotiv) [30], have reduced the design overhead of ad hoc prototypes for BCI studies[20]. Besides the usual discomfort and fitting issues, such **rigid** devices fall short as the proprietary system makes it impossible for the wearable community to integrate them into multi-modal, ergonomic, and aesthetic designs.

Open-source toolkits such as OpenBCI provide hardware and software suites integrating EEG Analog-Front-End (AFE) in a complete embedded system, compatibility with several types of electrodes, and flexibility to measure brain signals at any location on the scalp. Yet, OpenBCI has only seen limited adaptation among wearable researchers and smart garment designers outside the BCI community due to the low compatibility of the processor and software layers together with relatively high entry barrier and overhead. Additionally, its full-stack solution also has difficulty keeping up and integrating with the latest advancements in sectors like microprocessors, communication, and software.

[1]https://github.com/jufvargasco/Brainwear2.0

The true wearable EEG enabler is the **latest generations of chips** integrating EEG-level AFE, such as the ADS1299 (Texas Instruments) that integrates the entire 8-channel AFE in a compact package, replacing traditional cumbersome circuit assembly.[2] Several studies [11, 27, 30] have concluded that the ADS1299 reference design provides data on par with medical-grade systems.

In neuroscience, discarding the signals contaminated by **motion artifacts** is a common practice[5, 17], as muscular, ocular, and cardiac activities are coupled with electrical signals surpassing the surface EEG magnitude. However, these signals can also be interesting for HAR purposes. Facial muscular activities, for example, are shown to be relevant for emotional control [2], motor planning [28], emotional expressions [36], reading activities [21] and snacking moments [29, 37]. With the latest dry and textile electrode breakthroughs such as [1, 10, 32], the combination of multiple sensors to detect muscle movements in parallel with EEG is the apparent way forward [13, 29].

3 COMMUNITY-ORIENTED HARDWARE

The Brainwear EEG module's major design considerations are simplicity and compatibility. Simplicity by packaging all and only the necessary components for EEG sensing so that designers can use it as a plug-and-play module; and compatibility with the open and popular standards to not be locked-in by legacy technology. We positioned Brainwear as a plug-and-play part of the broader wearable system options so that EEG-enabled devices can easily benefit from the latest advancements such as faster processors, more efficient wireless communication, edge computing acceleration, and beyond.

As shown in Fig. 1, enabled by ADS1299[15], the Brainwear module handles up to 8 EEG channels and output the digital data by the SPI bus. More channels can be achieved by either daisy-chaining on the same SPI bus or adding modules on more SPI buses, depending on the host microprocessor's capability. Brainwear is designed to be footprint and pin-compatible with the Adafruit Feather family, which contains over 100 different modules with the same board footprint. Feathers are programmed with the Arduino software environment, which means a wide selection of microcontrollers can drive the Brainwear module with the same code. Even if designers choose microcontroller modules outside the Feather family, Brainwear can still be easily integrated by plugging into the SPI bus with minimal code modification, including OpenBCI.

The design, including technical specifications and board manufacturing files, together with the Arduino C library and examples, are all available on GitHub, so the entire wearable community can easily reproduce and integrate into their designs and studies.

4 PROTOTYPE VALIDATION

We first validated our approach with a soft EEG cap prototype [3] and the standard benchmark N-back test, through a study based on the common approach in neuroscience [8, 16, 26].

[2]OpenBCI Cyton and [7] both use ADS1299 with the chipmaker's reference design
[3]To validate the soft EEG cap with a cognitive study while performing in parallel the printed circuit board design process. In this prototype, we used Cyton (OpenBCI), which uses the same reference design as the ADS1299. The later signal level comparison showed no distinguishable difference between Brainwear and Cyton

Table 1: Summary of recent studies using mobile EEG for psychological studies and Human Activity Recognition

Application	Activities	Sensors and biosignals	Classifier	Accuracy	
Emotions	valence, arousal, happiness, fear, and excitement	OpenBCI (EEG) Empatica4 (EDA, skin temp, PPG)	k-means clustering	67% valence 70% arousal	[22]
	valence, arousal, and dominance	Emotiv EPOC (EEG) SHIMMER (ECG)	SVM	62 average	[18]
	Anxiety (3 different levels)	MindWave Mobile (EEG) PPG-fitted glasses (PPG)	KNN	62.5%	[35]
	Stress	MindWave Mobile (EEG) SHIMMER (EDA) BioHarness 3 (ECG)	SVM	86%	[3]
Cognition	Mental workload (0,1,2,3 - back)	Emotiv EPOC (EEG)	SVM	81% (0 vs 1/2/3-back)	[34]
	Drowsiness and Fresh state	Muse (EEG, IMU)	SVM	92%	[24]
Emotion/ cognition	Success in a learning task	Emotiv EPOC (EEG) Tobii Tx300 (Eye movement) FaceReader 6.0 (Expression)	Logistic regression	66%	[12]
Motion	Hand movement speed and position (fast-right, fast-left, slow-right, slow left)	Emotiv EPOC (EEG) V120 Duo (Limb motion)	LDA SVA	73.72% Only speed 69% left/right movement	[28]
Daily activities	Reading, speaking, watching TV	Muse (EEG)	FCEA framework	94.60%	[29]
Dancing	Neutral, think, and do Laban efforts (17 classes)	BrainAmpdDC (EEG) OPAL (Body kinematics)	LFDA + GMM	59.4% 3 classes 88.2% 17 classes	[9]
Cognitive + motor tasks	Relax, visual task, auditive task + 7 motor tasks (organizing books, standing up, salute motions, clapping, etc.)	Enobio (EEG) Rokoko (IMU)	Random Forest Gradient boost	96%	[13]

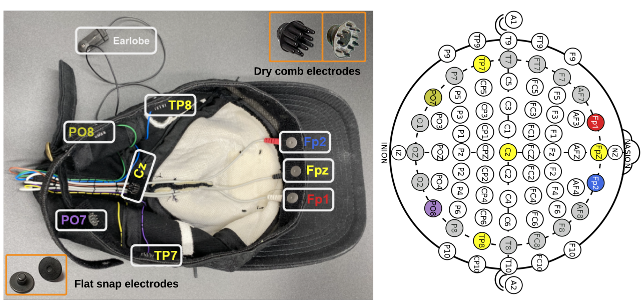

Figure 2: Soft EEG cap and electrode placement.

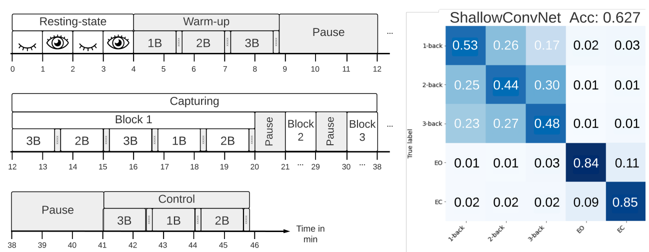

Figure 3: Experiment procedure and result.

4.1 Validation Method

Based on the analysis performed in [25] about the regions involved in memory workload and the 10-20 system [19], we located the dry electrodes at approximately evenly spaced locations at the prefrontal cortex (FP1, FP2, and FPz), the premotor cortex (Cz), and intersections between the temporal and occipital lobes with the parietal lobe (TP8, TP7, PO8, and PO7). Flat electrodes for hairless regions and comb electrodes of 2 or 5 mm long prongs for hairy regions are used depending on the participant’s hairstyle. [4] The integrated cap and the electrode placement is shown in Fig. 2.

Five healthy participants with university education (2 females, 3 males) between 23 and 30 years of age (mean age 26) took part in the experiment. All subjects were right-handed, had a normal or corrected-to-normal vision, and were naive to the nature of the experiment.

The experiment goal is to classify five different levels of memory workload: resting state with eyes closed (EC) and eyes opened (EO), and three states with increasing memory load: 1-, 2-, and 3-back. The single n-back task (Brain Workshop) with visual stimuli was used to induce cognitive load and benchmark working memory.

[4]Such dry electrodes are available from Florida Research Instruments Inc, Unicorn-BI, Neurospec, etc.

Fig. 3 shows the time course of the experimental procedure, containing five pseudo-randomized iterations of the three n-back levels. Each participant finished two sessions with a total of 4 minutes for each resting state and 21 minutes for each n-back level. The experiment was presented on a 24-inch monitor located at about 50 cm distance from participants and took place in one of the experimental rooms of the DFKI.

The signal processing and machine learning pipeline are based on the mature consensus and state-of-the-art in neuroscience [34]. The 8-channel 250 Hz raw signal was upsampled to 256 Hz by applying an FIR anti-aliasing filter. Then, the DC offset was removed by a high-pass filter with a cutoff frequency at 0.5 Hz. Moreover, a notch filter was used to remove the line noise at 50 Hz. The processed data was segmented into non-overlapping 2s windows. For n-back states, only the windows in the *Capturing Stage* (Figure 3) are used as the participants are properly engaged.

We employed a CNN-based deep neural network model commonly used in EEG signal classification: the Shallow ConvNet [31]. [5] Leave-one-session-out cross-validation was performed. Weight-assignment was used to tackle the data imbalance between idle states and engaged states.

[5]The model was taken from the Army Research Laboratory (ARL) EEGModels project https://github.com/vlawhern/arl-eegmodels, adapted to our data.

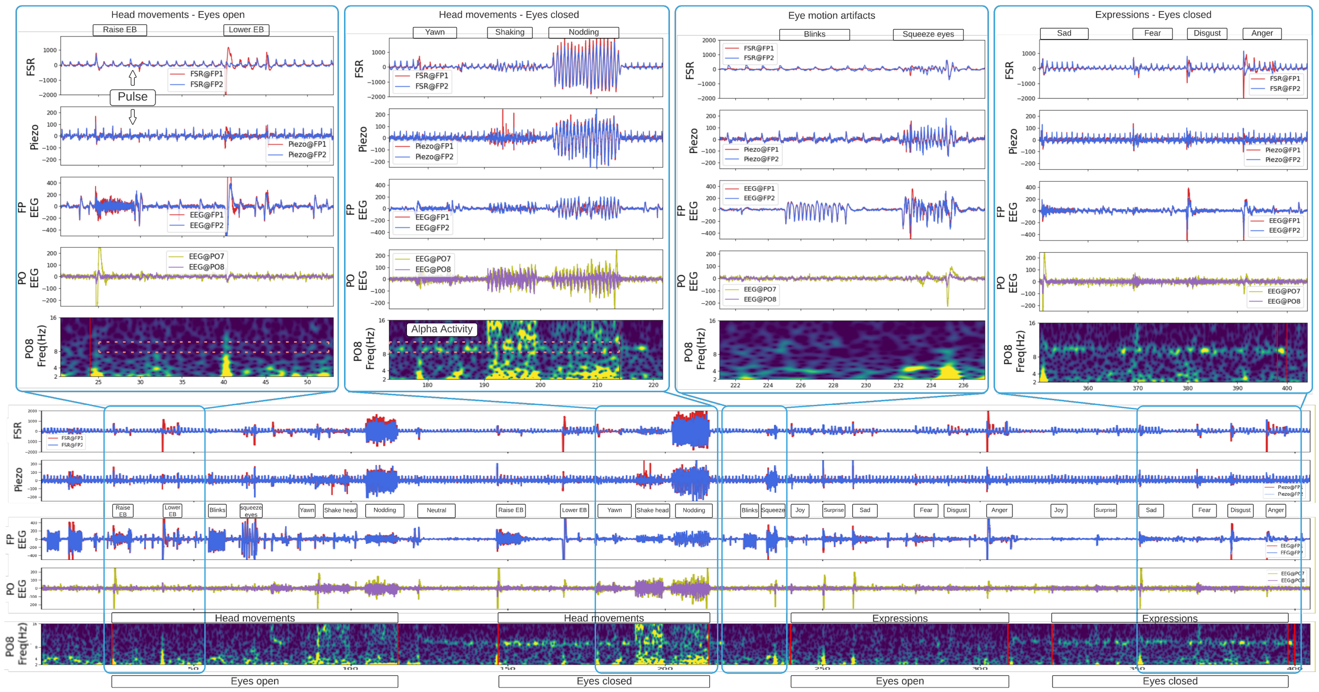

Figure 4: Person wearing the multi-modality cap while performing head movements and facial expressions with eyes closed and eyes open.

Table 2: Comparison with the neuroscience related work

Studies	Device	Memory workload levels	Classification method	Accuracy 2s window
Grimes et al. [14]	Biosemi activetwo (32-ch)	0 to 3-back (letter, image, spatial tasks)	Naïve Bayes (2-classes, 4-classes)	30% (4-classes)
Brouwer et al. [6]	g.tec USBamp (7-ch)	0 to 2-back letter task	SVM (binary)	68% (2-classes) (0 vs. 2-back)
Wang et al. [34]	Emotiv EPOC (14-ch)	0 to 3-back (letter, spatial tasks)	SVM (binary)	81% (2-classes) (0- vs. 1/2/3-back)
Proposed method	DIY cap (8-ch)	EC, EO, 1 to 3-back spatial task	Shallow ConvNet [31] (5-classes)	**63% (5-classes)** > 83% binary (rest vs. 1/2/3-back)

4.2 Results and discussion

The results are shown in Fig. 3 as confusion matrix and compared with other neuroscience literature in Table 2. The proposed method exhibits performance matching or exceeding the related works. The resting state (EO, EC) and cognitively engaging state (1/2/3- back) are well separated. EO and EC are also well distinguished. Although there are more misclassifications among 1/2/3-back levels, the result agrees with the neuroscience observations.

Overall, we can conclude that the EEG sensing system based on the ADS1299 reference design in the form of a daily garment - a soft cap, achieves similar levels of recognition as other neuroscience studies with dedicated instruments.

5 FURTHER GARMENT INTEGRATION

To demonstrate how easily Brainwear can be integrated with other sensing modalities, we expanded the prototype with two more sensing modalities at two sensing nodes (FP1/2) in Fig. 2.

With the Brainwear module, the improved cap is built around a Feather Huzzah32 module with the ESP32 microcontroller. An FSR and a piezoelectric sensor are stacked with the EEG electrode as shown in Fig. 1. A separate quad-channel ADC (TI-ADS1015) drives the FSR and Piezo sensors at 125 Hz and communicates with the microcontroller with the I2C bus.

A brief recording of a person wearing the multi-modality cap performing various head movements and facial expressions is shown in Fig. 4. The cap can detect well-known neural processes such as the "Berger effect" [20] that exhibits an increase in the posterior alpha frequency power (8 - 12 Hz) when closing the eyes. The figure also shows that the FSR and piezo reveal Ballistocardiogram (BCG) activity on the forehead together with gross motion characteristics such as nodding, shaking the head, yawning, and squeezing the eyes. These results agree with previous studies in which piezoelectric sensors were used to detect BCG and subtle movements or muscle contractions in the face [5, 33]. The latter study demonstrated how such activity can be decoupled from neural signals employing an adaptive filter. As [36] discovered, such forehead muscle mechanomyography can detect different expressions such as surprise, sadness, anger, among others. In our example, we can also observe distinct characteristics with different expressions, which could offer information on the wearer's facial expression, whereas the EEG data would have been discarded as a motion artifact in neuroscience.

6 CONCLUSION AND OUTLOOK

To conclude, we consider EEG to be a plug-and-play part of a more extensive customizable multi-modal wearable system. We developed an open-source, transparent EEG sensing module that is pin-compatible with the Feather family and protocol-compatible with an even broader scope of embedded processors. A garment prototype validation taken from the standard neuroscience and BCI literature shows that a soft EEG cap achieves performance on par with neuroscience state-of-the-art. Further integration with mechanomyography shows how EEG and other sensing modalities can be integrated into one wearable system, even at the same sensing location, to provide complementary information about the wearer's neural and physiological activities.

We believe our approach will enable more out-of-the-lab research opportunities that combine neural and physical activities, such as cognitive processes during sports activities.

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