Brain.me: A Low-Cost Brain Computer Interface for AAL Applications

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Abstract A Brain-Computer Interface (BCI) is an alternative/augmentative communication device that can provide users (for example, individuals lacking voluntary muscle control) with an interaction path, based on the interpretation of his/her brain activity. In this paper, the design and implementation of a flexible, low-cost BCI development platform is presented; this platform could serve as a workbench to develop compact, standalone BCI embedded modules, specifically targeted to (even if not limited to) AAL control purposes. First, a low-cost, custom, bio-potential acquisition unit was realized; then, a Matlab-based environment was developed for EEG (ElectroEncephaloGram) signal analysis and processing. An application example involving a 4-class SSVEP-based BCI is presented, along with a novel classification algorithm which achieved 94.7 % classification accuracy.

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1 Introduction

Ambient Assisted Living Technologies (AAL) aim at making the home environment more cooperative and intelligent, providing help to accomplish daily living tasks; AAL solutions have been successfully applied for supporting and promoting independent life of elderly people. However, individuals affected by severe impairments could be potential beneficiaries of AAL services too (such as those aimed at environmental safety and control): the main issue is to provide these users with an effective interaction path to the AAL system.

A possible approach to this problem involves Brain-Computer Interface (BCI) technologies. BCI are alternative/augmentative communication means [1] that aim at providing the user (for instance lacking voluntary muscle control) with an interaction path, based on the interpretation of her/his brain activity. In this paper, the development of an EEG (ElectroEncephaloGram)-based BCI communication unit is introduced, explicitly conceived for (even if not limited to) AAL control purposes. Therefore, with respect to most common BCI approaches, the proposed strategy focuses at relatively simpler tasks, leaving room for lowering costs, user's effort and invasiveness.

In our view, the BCI device must be seamlessly integrated into CARDEA [2], the flexible, LAN-based, AAL system developed by the University of Parma. CARDEA, like most common home automation systems, offers environmental control and safety services, but, in addition, it provides more advanced functionalities, related to Assistive Technologies (AT): examples are fall detection, vital sign monitoring [3] and indirect wellness monitoring [4]. Thus, CARDEA integrates both AT and AAL aspects under a unique, convergent vision.

In order to provide such services, CARDEA currently supports many user interaction paradigms, including button switches, touchscreen, vocal, remote internet control; in [5] the interaction scheme between CARDEA and a simple BCI is discussed. Other examples of AAL-focused BCI can be found in [6–9]. With respect to most literature works, the present approach aims at developing tools and methods for low-cost, standalone embedded BCI modules, making high-performance acquisition hardware or large computing powers unnecessary.

In this paper we describe the development of a platform conceived for prototyping of BCI embedded system; it includes three main units (Fig. 1): (i) an Analog Front End (AFE) for the acquisition EEG signal, (ii) a digital signal processing unit, implementing feature extraction and classification and, (iii), an output/feedback unit for display and implementation of active controls. We started from developing and testing a novel hardware AFE unit, aiming at a compact and inexpensive circuit. Signal processing and feedback units are currently implemented on a PC architecture, allowing for more flexibly testing and for better tuning performance. Nevertheless, the algorithms are specifically targeted for implementation on low-cost, portable devices, paying attention in devising computationally efficient methods.

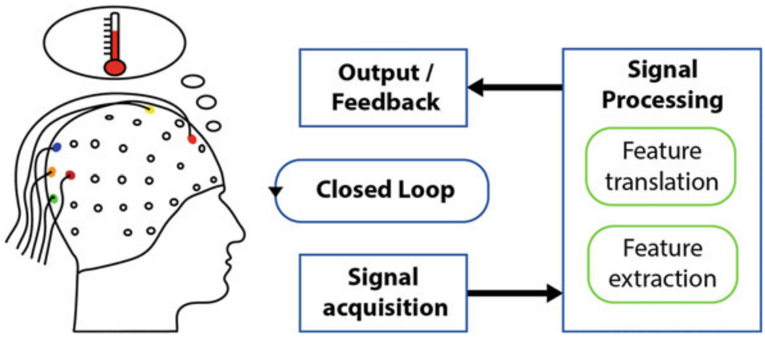

Fig. 1 Functional blocks of a BCI

Such environment enabled testing of different configurations, algorithms and methods: among them, a novel Steady State Visual Evoked Potentials (SSVEP) classification algorithm was devised, yielding good performance and requiring no initial user training. This allows for simplifying the overall design and also fosters its portability to different configurations. Eventually, all these functional units will be integrated in a compact, standalone embedded module, capable of local and autonomous signal processing, which will interface to the AAL system as a simple controller.

In Sect. 2 an overview of the proposed module is presented, demonstrating its capabilities and flexibility; Sect. 3 presents an application example of the BCI module using the Steady State Visual Evoked Potentials (SSVEP); finally, in Sect. 4 the results obtained in the previous section are presented and discussed, as well as the future work.

2 Overview of the Proposed BCI Module

Although many different methods can be used to extract information on the user's brain activity, such as the ones based on functional Magnetic Resonance Imaging (fMRI) [10], Near InfraRed Spectrography (NIRS) [11] or Positron Emission Technology (PET) [12], EEG is the most popular technique for practical BCI devices. In fact, EEG signals can be non-invasively acquired from the scalp, by sensing the electrical signal with (dry or wet) skin-surface electrodes. Moreover, given our purposes, EEG offers a satisfactory tradeoff between spatial and temporal resolution, as well as reasonable costs and compactness when compared to other methods.

As far as communication paradigms are involved, focusing on EEG-based BCI, many brain features can be exploited. Among the most popular ones we can cite: Slow Cortical Potentials (SCP) [13], Event Related De-synchronization (ERD) [14] and the related motor imagery paradigm, P300 [15, 16], Steady State Visual Evoked Potentials (SSVEP) [17]. The latter paradigm, in particular, exploits brainwave features elicited by the involuntary response to a continuous, repetitive stimulus, such as a blinking LED: within a given low-frequency range, the blinking frequency reflects on the onset of a isofrequency component in the brain power spectrum. With respect to other paradigms, the SSVEP paradigm makes synchronization issues less critical, and possibly lends itself for simpler acquisition architectures.

High-end, clinical EEG equipment with a large number of electrodes are scarcely suitable for the design of low-costs, small-size devices. In [5], an inexpensive EEG Analog Front End (AFE) module for extracting basic information on brain activity was presented; this module was realized using low-cost, standard electronic components to foster product interoperability.

In order to cope with such extremely small signals (whose amplitudes are as low as a few μV) low-noise design techniques were applied. In particular, signals had to be amplified before digitization, in order to prevent the ADC's (Analog to Digital Converter) noise floor from corrupting the informative content in the EEG waveforms. Obviously, the amplification chain should contribute as low noise as possible on the desired signal. This calls for AC-coupling and high gain applied to the input waveforms (intrinsic DC offset between the electrodes prevents from applying a high DC gain). Moreover, EEG signals generally exhibit poor Signal to Noise Ratio (SNR) due to, for example, electrical and power line interference. The use of active electrodes helps in mitigating those issues, having better performance than their passive counterparts, but this comes at the price of increased costs and complexity. Given the purpose of our work, focused more on cost effectiveness and versatility, we adopted passive electrode technology; this choice, however, does not preclude future deployment of different types of sensing elements.

Given the requirements discussed above, a multi-channel AFE for EEG signals was designed and realized on a standard 4 layer PCB. The module, which can be operated both in single supply or in split supply mode, features up to 6 differential/common reference EEG-specific channels, plus 2 spare, fully-differential channels. These additional channels can be used, for example, for simultaneous recording of other biopotentials, such as ElectroOculoGram (EOG), ElectroMyoGram (EMG), ElectroCardioGram (ECG); in this way, new types of analysis can be carried out, relating different biopotentials. Examples could be the correlation between the recorded EMG at the onset of a movement and the correspondent ERD in the sensorimotor cortex, or the detection of ocular artifacts by means of EOG signals.

Figure 2 shows the schematic of an EEG acquisition channel along with a Driven Right Leg circuit, introduced to improve common mode noise rejection. Each channel features a differential, passive AC-coupling stage, whose components do not affect the overall Common Mode Rejection Ratio (CMRR), nor their contributed noise impact significantly on the overall performance [18]. A differential, AC-coupled amplification stage applies a gain of 800 to the input EEG waveforms, and a second order, Bessel-response low-pass filter with a cutoff frequency of 250 Hz follows to limit the signal bandwidth: this value was chosen in order to allow easy recordings of other biopotentials, such as ECG. A high resolution 24 bit $\Sigma - \Delta$ ADC completes the signal chain.

Noise performance of the AFE was tested with input terminals shorted and the input referred noise was less than 1.8 μVpp, more than sufficient, in principle, to

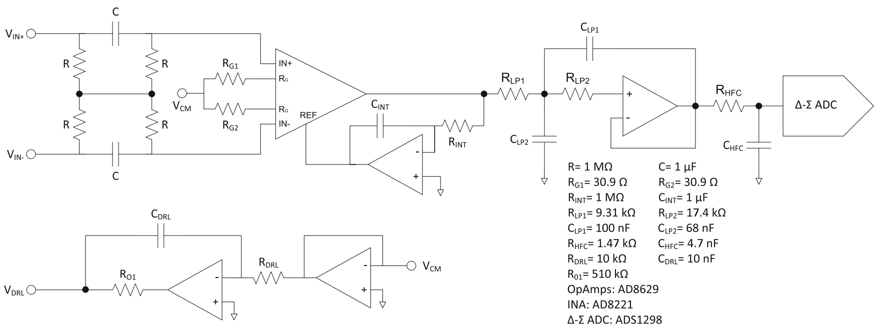

Fig. 2 Schematic of the proposed AFE

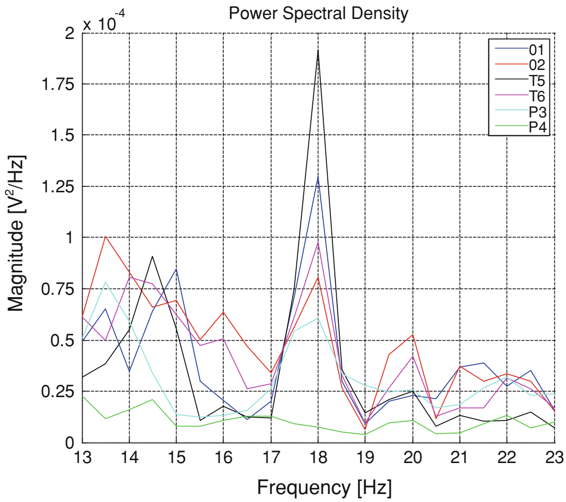

Fig. 3 Example of an 18 Hz SSVEP response. Electrode locations are reported in the legend

extract basic information of brain activity. As an example of functional validation, a Power Spectral Density (PSD) plot of an 18 Hz SSVEP response, acquired with the proposed AFE, is shown in Fig. 3; spectral peaks at the corresponding stimulation frequency are clearly visible.

At this stage of research, a Matlab-based platform for paradigm testing and algorithm prototyping was designed. From such environment, we can control several AFE parameters, such as ADC gain and data rate, as well as interact with the controllers of the stimulation units, such as flashing lights or arrays. Matlab-ADC interfacing is achieved by means of an Arduino Board, communicating via serial protocol. TCP/IP support is currently being developed.

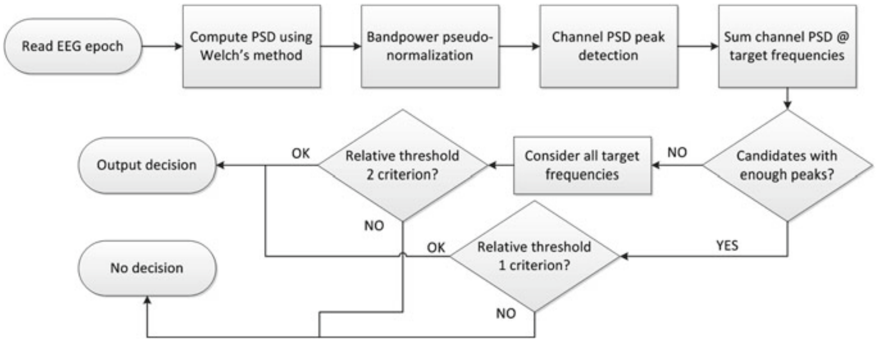

Fig. 4 The proposed lightweight, calibration-less SSVEP classification algorithm

3 Application Example: 4 Class SSVEP BCI

As an application example, a 4-class SSVEP BCI is presented, based on a novel, lightweight classification algorithm suitable for implementation on low-power embedded processors.

The experiment was devised as follows: participants were asked to stare at one of the four simultaneous flickering LED while resting on an armchair at approximately 1 m from the visual stimulus. Each trial lasted for 6 s, and each LED presented a different stimulation frequency (16, 18, 20, 22 Hz); EEG was acquired at 250 SPS from 6 scalp locations (namely O1, O2, T5, T6, P3, P4), using standard 10 mm Ag/AgCl disk electrodes with conductive paste.

In order to classify the SSVEP response, a novel algorithm was developed and tested, illustrated in Fig. 4.

First, the input EEG waveforms are low-pass filtered ($f_{cut} = 40$ Hz) for out-of-band noise reduction. Optionally, further pre-processing steps may include spatial filtering, such as a re-referencing of electrodes according to Common Average Reference (CAR) filter topology, or the creation of bipolar leads. Then, the Power Spectral Density (PSD) is estimated using Welch's method. At this point, given a pre-determined band of interest, the channel powers are equalized over this band.

The classification algorithm exploits the *a priori* knowledge of the actual set of stimulation frequencies, checking the conditions only on such set: the channel powers are summed at each target frequency. Candidate targets are selected whenever a given fraction (e.g., at least 50 %) of the channels exhibit a local maximum in the PSD at the target frequency. Then, candidates are compared; a two-step procedure has been devised: if a single candidate exists, the power of which exceeds all the remaining ones by a given threshold, the decision is made. Otherwise, a more selective comparison is made, considering all the target frequencies as candidates and raising the threshold.

Since the test involves only relative comparisons, the algorithm virtually requires no calibration at all. Fine tuning of the algorithm is obtained by adjusting theclassifier's

Table 1 Performance of the proposed algorithm as a function of the window length in terms of correct classification percent and, between brackets, ITR (bit/min)

	Window length			
Subject	3 s	4 s	5 s	6 s
1	90.0 (27.45)	83.3 (16.27)	86.7 (14.66)	90.0 (13.73)
2	91.7 (29.08)	91.7 (21.81)	100 (24.00)	100 (20.00)
3	87.5 (25.17)	95.0 (24.52)	92.5 (17.96)	97.5 (17.92)
4	94.1 (31.68)	94.1 (23.76)	94.1 (19.01)	91.2 (14.31)
Average	90.8 (28.35)	91.0 (21.59)	93.3 (18.91)	94.7 (16.49)

parameters, such as the fraction of channels required to pick a candidate frequency or the relative thresholds for comparing candidates as discussed above.

Moreover, signal processing involves operations particularly suitable for implementation on embedded devices, allowing to take full advantage of specialized digital signal processing hardware.

4 Results and Discussion

To evaluate performance of the aforementioned classification algorithm, experiments were conducted on four healthy volunteers (age 23–26, with normal or corrected to normal vision, five of them without any prior BCI experience); examples of acquired SSVEP responses are shown in Fig. 3. The algorithm was then tested on different window lengths in order to assess and optimize its performance. Two main indicators are usually considered in evaluating BCI setups:

- *Accuracy*, defined as the number of correctly classified trials over the total number of attempts
- *Information Transfer Rate* (ITR), defined in [1] as:

$$ITR = M\left[\log_2 N + \mathrm{P}\cdot\log_2 P + (1-P)\cdot\log_2\left(\frac{1-P}{N-1}\right)\right] \tag{1}$$

where M is the number of trials per minute, N the number of possible choices, and P the classification accuracy.

Table 1 summarizes the performance of the proposed algorithm in terms of accuracy and ITR, assuming a decision is made every *Window Length* seconds.

Even though the approach is intentionally simple, experiments showed that a maximum average accuracy of 94.7 % was achieved, making it practical for aimed AAL control purposes. Such accuracies are in line with state of the art multi-class SSVEP-based BCI. Higher classification speed (i.e. ITR) can be obtained at the price of more computationally intensive signal processing, such as in [19]. However, with respect to most works in literature, focuses on the development of compact, low-cost tools for researching and experimenting novel BCI algorithms, with a particular effort in producing computation-efficient methods, suitable for implementation on low-cost embedded systems. Furthermore, it is worth emphasizing how, focusing on AAL system control purpose, the accuracy of the selection process is actually more important than the selection speed.

The introduction of band-power normalization is shown to slightly improve the classification performance, especially in case of a strong inter-channel imbalance, due to, for example, different electrode impedance; the normalization improves the classification robustness by somehow self-adapting to variable scenarios.

In addition, the proposed algorithm is relatively simple and suitable for implementation on low-power, mobile digital processors, such as DSP or ARM microprocessors. Finally, it does not require synchronization between the stimulation and the acquisition unit, thus simplifying the overall design of an embedded BCI system. Further optimizations will lead to a compact, embedded system capable of processing the signals locally, and handling all the communication in a unique module.

Basic, cue-based online operation is supported, while online, self-paced operation is currently being investigated to provide the user with more flexibility and classification speed.

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