An integration of Brain-Computer Interfaces with an Alternative Augmentative Communication System

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Abstract. People who cannot communicate with others or that have great difficulty in doing so are usually dependent beings and suffer from social isolation. There are multiple systems and tools that enhance the communicative interactions, called Alternative and Augmentative Communication Systems (AACS). In critical situations, where no voluntary movements are available, Brain-Computer Interfaces (BCI) start to take part. BCI's are devices that allow a person to interact with a computer using only their neuronal activity. BCI's have been studied for more than 30 years, but their high error rate and the complexity of the systems have always been challenges when implementing functional real-life solutions. The current work includes a review of the BCI Emotiv Epoc, a wireless, low-end, EGC device that tries to bring medical-lab technology to the users' home, as well as the development of a custom application to connect it to a well-known AACS: ACAT.

Keywords: Brain-Computer Interface, BCI, Alternative and Augmentative Communication, AAC, ACAT, alpha rhythm.

1. Introduction

According to Escandell [1], communication is a complex activity involving various types of entities, representations and processes: the sender intentionally produces a symbolic expression and offers it as an indication of his communicative intention. The receiver, on the other hand, has to decode the linguistic expression and infer the relationship between the indicative clue and the sender's communicative intention in order to recover the representations that the sender wanted to communicate, using heuristic processes that try to find a plausible explanation from the available data.

These data include individual representations, but also representations widely shared by the members of a given culture and/or social group, which largely condition the way of perceiving and reacting to the environment. There are several types of problems that can affect the communicative ability of a person: speech disorders (like dyslalia, dysgnosia, rhinolalia, Dysphemia, tachyphemia, dysphonia or aphonia), oral language disorders (like language delay, aphasia) or written language disorders.

People who cannot communicate with others or that have great difficulty in doing so are usually dependent beings and suffer from social isolation. There are multiple systems and tools that enhance the communicative interactions, called Alternative and

Augmentative Communication Systems (AACS). AACS complement oral language when all by itself is not sufficient for effective communication with the environment, and replace oral language when it is not understandable or absent.

In critical situations, where the person has no voluntary movements or they are severely restricted, Brain Computer Interfaces (BCI) enter the scene. BCIs are devices that acquire and measure brain activity, process and classify these signals to produce a digital output that can be used to perform tasks such as moving a cursor, using a computer or enabling/disabling external actuators (like steering a wheelchair) allowing the person to interact with a computer using only their neuronal activity.

The present article has two main axys: The first one centered on an analysis of different software AACS and the Emotiv Epoc BCI, and the second on the development of a prototype that integrates the BCI with ACAT. Also, it explains the difficulties found and the main solutions developed to achieve this complex process.

2. Motivation

BCI's have been studied for the last 30 years with the main objective of providing assistive technology for people with severe physical functional diversity, but the complexity, slowness and the high error rate have been challenges when implementing real-life solutions. The recent progress in biosensor technology and computing scale and performance have improved the position of BCIs, making them not only viable as assistive technologies but also plausible of being used as everyday artifacts. They have transcended the limits of the lab and experimental technology and are now offered as commercial home-products or even toys.

During the last few years, we interviewed people from different organizations focused on the assistance and integration of people with different physical ailments and functional diversity, and we reached the conclusion that there's a severe lack of information regarding these technologies, their possibilities and the solutions they can provide, specifically about brain-computer interaction. Is difficult to find public or private institutions that develop new hardware, software or that contribute systematized knowledge about existing solutions.

In this context the motivation of the present work is to stimulate the development of these technologies in our near community through our university, the consolidation and systematization of knowledge about existing technologies with a multidisciplinary approach, collaborating with different institutions of our city.

3. Alternative and Augmentative Communication

As we stated earlier, there are several oral language disorders, cognitive or physical restrictions and sensory functional diversity that may affect the communicative ability of a person, and there isn't a generalized solution that works for every person.

Tamarit [2] defines AACS as logopedic instruments for people with different language or communication disorders; their objective is teaching a structured set of non-linguistic codes that would provide the person with the means to communicate spontaneously and autonomously in combination or not with other vocal or non-vocal codes. It uses different types of expression than traditionally spoken or written language and their purpose is to augment or counteract the difficulties in linguistic capacity of people with functional diversity [3].

The first categorization we can establish is differentiating Augmentative from Alternative Communication. The first one refers to systems designed to enhance a person's speech ability. The other one refers to systems designed to replace speech.

Based on the kind of external support the system needs, there are 2 types of communication possible: Communication with help and communication without help.

Communication without help occurs when the communication act is performed with the person's own body, without assistance of external object or medium. These kinds of systems are more frequently used by people with some kind of sensory functional diversity, like blindness or deafness. The most common communicative systems in this category are sign language, lip-facial reading and the Braille system.

Communication with help occurs when the communication act is performed using some external support. This kind of communication usually uses non-vocal, graphical communication systems, with symbols, and are usually used when the person has a

physical functional diversity (like progressive neuromuscular diseases, cerebral palsy, cranioencephalic trauma) or intellectual functional diversity. Examples of this kind of systems are the Bliss system (a symbolic graphical system) or SPC (spanish acronym for Pictographic System of Communication).

In the present work we will center in Systems that provide Communication with help. Particularly, we will analyze ACAT [4], a free, open-source, suite of applications specially developed by Intel for the physicist Stephen Hawking.

ACAT stands for Assistive Context-Aware Toolkit, is an open source platform developed by researchers at Intel Labs to enable people with motor neuron diseases and other disabilities to easily communicate with others through keyboard simulation, word prediction and speech synthesis. Users can perform a range of tasks such as editing, managing documents, navigating the Web and accessing emails, using a single Keyboard event (by default, F12 key press).

In Fig.1 (a) we can see its two main features: the Talk window (where the user writes what they want the system to read out loud), the Alphabet Scanner (where the user selects either a word from the text predictor or a letter from the alphabet to be added to the text).

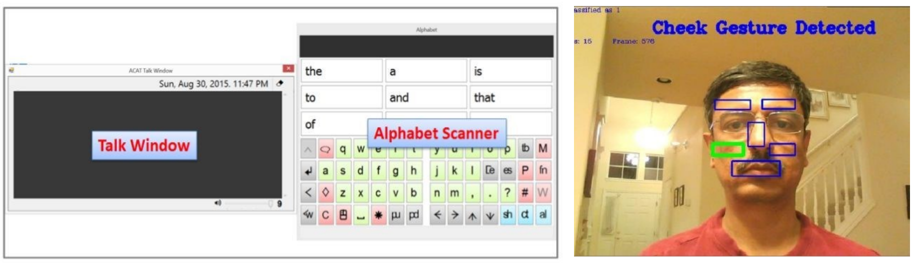

Fig. 1. (a) ACAT application board - (b) ACAT detected gesture región

ACAT also provides ACAT Vision, which acts as a virtual switch using face-tracking and movement detection algorithms on different parts of the face that can be used via an inexpensive webcam (see Fig. 1. (b)). ACAT is open sourced and provides extensive and complex features, so that it can be difficult to configure, setup or extend correctly for non-technical users.

4. Brain-computer Interfaces

A Brain-Computer Interface is a device that allows direct communication between the brain and a computer based on the brain's electrical activity. Nicolas-Alonso and Gomez-Gil [5] defined brain–computer interface (BCI) as a hardware and software communications strategy that empowers humans to interact with their surroundings with no inclusion of peripheral nerves or muscles by utilizing control signals produced from electroencephalographic activity.

By observing and mapping the brain electrical activity to images it is possible to identify patterns, zones in charge of certain cognitive processes. One of the more used and less invasive techniques to observe these is the electroencephalography (EEG) [6]. EEG records voltage fluctuations due to the flow of ionic current during synaptic excitations in the neurons of the brain [7]. They are recorded using electrodes attached to the scalp. Series of the reading of an electrode are called brain signals.

EEG is a non-invasive technique, is not expensive, and has a very good temporal resolution in the order of milliseconds.. It has two main drawbacks: the first is that it has poor spatial resolution as each electrode measures the activity of a big number of neurons; the second is that the signal quality tends to be noisy as it needs to pass through bone and skin and is easily interfered by external electro-magnetic radiation.

Anyway, these characteristics have made EEG the most popular modality among the BCI research community. The EEG brain signals can be categorized according to frequency bands: Delta (from 0.5Hz to 4Hz), Theta (from 4Hz to 8Hz), Alpha (form 8Hz to 13Hz), Beta (from 13 Hz to 30Hz), Gamma (higher than 30Hz). For this work, we are particularly interested in the alpha waves or alpha rhythm. Alpha waves can be measured reliably in the occipital lobes approximately one second after the person closes their eyes(see Fig. 2).

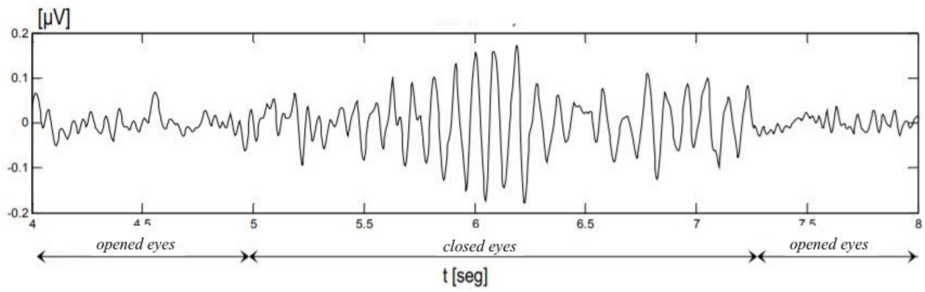

Fig. 2. Alpha rhythm visualization

It was first thought that the rhythm was a representation of the activity of the brain while the visual cortex was in stand-by mode, but more recent studies show that they either inhibit areas of the cortex that are not being used or are related to network communication [8] [9]. It is one of the strongest waves detectable on EEG, they are easy to produce and detect. This makes them frequently used for testing and diagnosing BCI hardware and software.

5. Emotiv Epoc

Emotiv Inc. is an Australian company that develops EEG-based Brain-Computer interfaces. The interface used in the present work is the Emotiv Epoc, recommended for investigation and complex applications (See Fig. 3 (a)).

Fig. 3: (a) Emotiv Epoc / (b) Emotiv Epoc Flex

The EEG has 14 channels using sensors AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 and 2 references: CMS/DRL references at P3/P4; left/right mastoid process alternative. Sensor’s material is saline soaked felt pads.

These should be cheap to produce and easy to replace, but our experience shows that the design is fragile, the pad supports are easy to break. A set of replacement pads cost us half the price of the whole device. The constant use of saline solution tends to corrode the electrical contacts thus making the replacement unavoidable in the mid term. To extend the life of the set we disassemble and thoroughly clean each pad after use, but the work is tedious and not very effective (Eg. by the end of this investigation, brand new electrodes were almost ready for a replacement again).

It is wireless and connects via low energy bluetooth using a custom 2.4GHz USB receiver. Having no cables hanging from one’s head is definitely good, but the headset is not really “mobile”. The connection is highly affected by distance and we observed the device needs a direct line of view from device to receiver to perform decently.

The EEG signals are acquired by sequential sampling using a single ADC and a sample rate of 128 samples per second (SPS). It could be raised to 256 SPS setting a special configuration in the hardware. The resolution it manages to obtain the data is 14 bits (16 bit ADC, 2 bits instrumental noise floor discarded). It also provides 9 axis motion sensors to detect head movement using an accelerometer and a magnetometer.

The software and drivers run on Windows, Mac, IOS and android (there’s no official Linux support, but there are some reverse engineered drivers that support the basic functions). The suite provides some neat screens to help with the setup of the headset where one can see the quality of the signal of every sensor, the status of the wireless link and battery of the device (See Fig. 4 (a)).

This app works really well and is really helpful, is always needed as part of the setup and lets you avoid re-implementing this kind of utilities in your custom app.

The software suite also provides detection of mental commands: neutral + up to 4 pretrained items per training profile. This is a really interesting feature but after training and using it for several hours, we couldn't find a way to reliably use the commands. Training 2 commands is exhausting. Training more is almost impossible: it looks like the training of a 3rd or 4th command somehow interferes with the detection of the first ones, so training more than 2 is very hard. It also calculates some metrics like excitement, engagement, relaxation, interest, stress and focus.

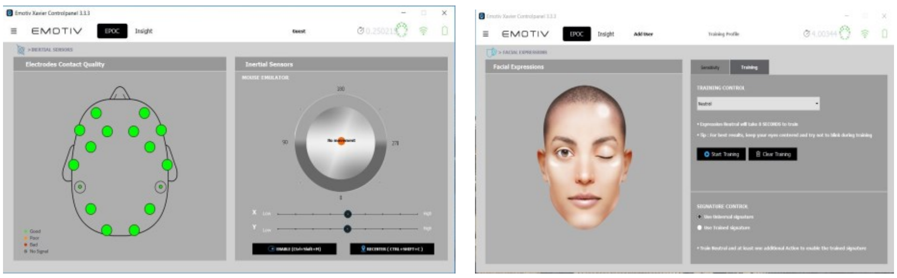

Fig. 4: (a) Signal sensors / (b) Facial expressions detected

It is also able to detect facial expressions like blinking or winking, surprise, frown, smile, clench, laugh and smirk (See Fig. 4 (b)). These detections work better than the mental commands but they are still flickery and our tests were full of false-positives (Eg. a blink benign triggered while the testing subject has his eyes wide open), with a proper noise reduction technique they should be usable to build some interesting interactions with the machine.

Finally, the most interesting feature for this work, although perhaps the more basic one: the pro license (paid) provides access to raw EEG signals, which is what we are going to use to build the integration with ACAT in the next section.

6. Custom Application Development

The objective of the prototype implemented here is twofold. On one hand, be the first practical approach to the Emotiv Epoc and its SDK in our university. On the other, serve as the base for future research and applications development.

So, the work focus is not just functionality, but also tooling. The application will read the raw signals from the Emotiv, process them to generate interaction events and send them to ACAT. We decided we were going to use the detection of alpha rhythm as the source of the events. From a technical standpoint, alpha rhythm is easy to detect with a high degree of confidence. Thanks to this, it is very used as a diagnosis tool and is frequent to find alpha rhythm detection on BCI software for hardware diagnosis purposes.

6.1 Signal Processing and Digital Filters

As we already mentioned, the signal received from an EEG is noisy. So the first step to use them is to process them to clean them and transform them into something useful. For this we will use a set of digital filters and transformations. Digital filters are mathematical operations that take a series of values (input signal) and modify it in some way and produce another sequence of values (output signal) with the objective of emphasizing or attenuating certain aspects of the input signal.

The algorithm we developed to detect the alpha rhythm and generate the keyboard event has 2 phases: a signal processing phase that consists of a set of composed filters functions (the output of one is the input of the next), and a detection phase, that analyzes the output of the processing phase to determine if the conditions to trigger an event are met using 2 configurable parameters (threshold and sensitivity).

6.2 Implementation

In order to verify the signal processing phase we developed a test mode that you can switch on/off at will. The advantage of the test mode is that it doesn't need the headset connected so we could avoid all the setup and sensor-caring activities.

When the test mode is turned on, the system takes the input signal from an alpha rhythm generator we programmed into the application. The generator creates a synthetic signal which mimics the synchronous activity of the neurons of the occipital lobe of a person opening and closing their eyes for several seconds in an endless loop. The test signal consists of a 10 Hz sinusoidal wave with a tiny amount of noise, which is interrupted by several seconds of white noise. Finally we add some low frequency sinusoidal movement (See Fig. 5).With this in place we could easily develop and test the filter chain and the detection algorithm.

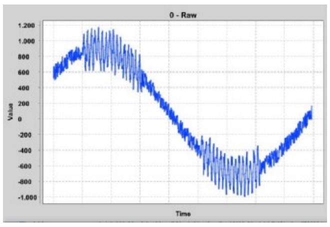

Fig. 5: The original input signal

The signal processing steps are:

- High-pass filter: This step removes all the low frequency noise. You can clearly see the signal has lost the low sinusoidal movement (See Fig. 9 (a)).
- Band-pass filter (8Hz - 12Hz): This step reduces considerably the amplitude of frequencies lower than 8Hz and higher than 12Hz, thus isolating the Alpha band we are interested in (See Fig. 6 (b)).
- Rectifier: This step converts the negative half of the wave to positive, so we now have a positive-only signal forming "10Hz mounds" (See Fig. 6 (c)).

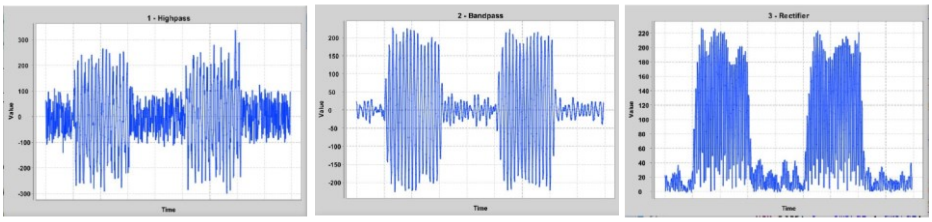

Fig. 6: (a) high-pass filter / (b) band-pass filter / (c) rectifier

- Low-pass filter*:* Here we remove the high-frequency movement and we keep only the profile of the mounds (See Fig. 7 (a)).
- Amplifier: This step elevates every value of the signal to the power of 2, thus making the amplitude of each 10Hz mound bigger, emphasizing the difference with those parts of the signal where we originally had noise (See Fig. 7 (b)).
- Threshold-based square wave conversion: in this last step, the signal is transformed into a square wave of amplitude 1 using a configurable threshold. Those places where the amplitude was greater than the threshold are converted to 1, those lower than the threshold to 0 (See Fig. 7 (c)).

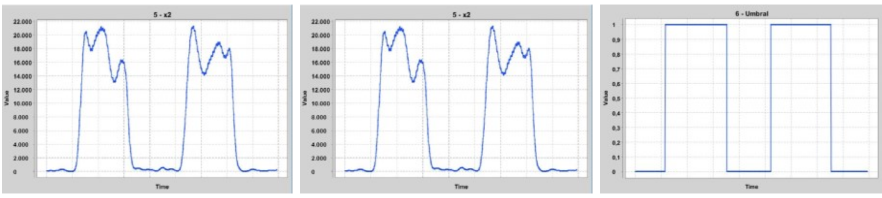

Fig. 7: (a) low-pass filter / (b) amplifier / (c) threshold-based square wave conversión

Finally, we can see the whole filter chain in action processing a real EEG signal taken from the Emotiv Epoc (see Fig. 8).

The subject closed their eyes 2 times in this sample (one on the very beginning of the sampled data, and the other near the end). Notice that the first event has a double peak mound, this kind of artifacts is quite common but the detection phase takes care of cleaning the out.

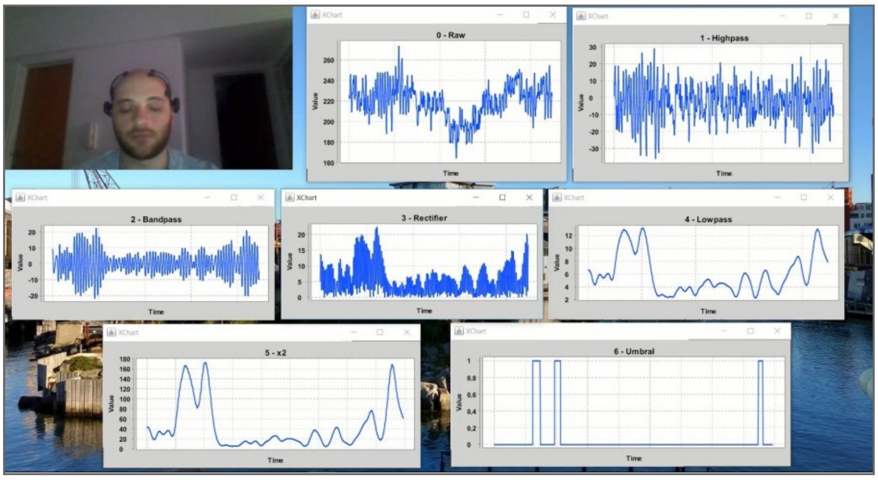

Fig. 8: Filter chain applied to a real EEG signal.

With the signal left by the last step of the signal processing phase the event detection is quite straight forward: counting consecutive 1's. The system then calculates the rate of 1's per second, and triggers a keyboard event and plays a sound if the rate surpasses a given amount.

When we started testing the first implementations of the detection algorithm, we found out that amplitude of the neural activity varies greatly from person to person or even from sessions to sessions of the same person on different days. This introduced the need to add a configuration tool from which we could easily control the detection algorithm parameters and quickly adapt the application responsiveness for the user's situation. The configuration tool developed has 2 parameters: threshold, that is the value of the threshold used in step 6 of the processing phase and sensitivity, that represents the rate of 1's the algorithm must detect in a given second before triggering an event. The values for the threshold can only be obtained by connecting the headset doing 2 or 3 tries and using an average value. We found out that a value around 60% of the max amplitude of the mounds in step 5 works ok most of the time. Regarding sensitivity, usually what is preferable of this type of interfaces is that they were hard to trigger but precise, rather than being full of false-positive non desired "clicks". Thus, having values above 75% is what we found more effective. The 2 parameters have a deep inter-relationship but proved to be sufficiently flexible. For example having 100% sensitivity means that we would need a complete second full of consecutive 1's, which due to the noisy nature of the EEG signals might be hard to obtain, unless you use a very low threshold.

6.3 Integration Testing

ACAT is very powerful, it provides a lot of tools and different mechanisms to control the computer and its programs. All of these tools are available to any device that can trigger a keyboard event (F12 keypress, by default).

The downside is that the configuration is also huge, and knowing how to really use every one of the applications can take a lot of time. Another drawback we found, is that the configuration of the screen scanners delay has a maximum allowed value of 3 seconds and our detection algorithm has a latency between 3 and 5 seconds. This is due to the nature of the alpha rhythm (a person needs to close their eyes for 1 or 2 seconds for it to appear) and the amount of samples we are using to trigger the keyboard event to prevent false positives. This makes us think ACAT is built with a faster and more precise triggering mechanism (for example, Stephen Hawking used it with an infrared sensor in his cheek, which reacts in the order of milliseconds). So the tests we performed resulted in an extremely wearing experience.

Functionally speaking, the integration was seamless, needing a single keypress makes the task really easy. The integration was usable in an ACAT Speller, a training app, that allows up to 5 seconds delay per option in the screen scanner. Also tried it with some board games like tic-tac-toe, and the application gave success results.

It is still a slow reacting control interface. We think the combination of a faster evoked potential (like p300 for example, which takes around 300 milliseconds to appear) and the ACAT intelligent autocompleter (which stores the most used words in a personal dictionary) is viable to have a better user experience and a more responsive interface.

7. Conclusions

This paper presents a custom application development to make an integration of Emotiv Epoc with ACAT tool. This prototype reads the raw signals from the Emotiv, processes them to generate interaction events, and sends them to ACAT. The algorithm was developed to detect the alpha rhythm and generate the keyboard event in 2 phases: a signal processing phase, and a detection phase.

While doing this investigation and development with social implications, we found the complexity of this kind of technology and their integration in order to help people to better communicate using these systems. Applications like ACAT are really complex, not easy to use or configure and have a steep learning curve for non-technical people. But once this curve is surpassed the amount and quality of the tools it provides is excellent.

On the BCI side, we find the Emotiv EPOC not a good fit to use as a every-day home device. The electrodes dry up really quickly. In order to moisten them again, you have to remove the headset and then recheck the connectivity and quality signal of each of them. Signal quality and wireless range is not really an enabler as the user cannot be far away from the computer. Perhapsa wired device could improve the signal quality and stability. work performing the integrations with AACS.

More testing and validation processes where to analyze the use and impact of this technology will be done in future works.

Finally we want to conclude that learning about filters, their implementation and application, and the integration with software such as ACAT was very enriching. We believe that this research is the starting point in our University for the advance of BCI development.

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