

A LOW-COST EEG STAND-ALONE DEVICE FOR BRAIN COMPUTER INTERFACE

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Abstract: This paper describes the ongoing development and design of a portable and stand-alone EEG device to be used as a Brain Computer Interface (BCI) for wheelchair steering. The overall system comprises the EEG (electroencephalogram) amplifier, data acquisition, communications and stimuli generator. The main attractive feature of this system is its stand-alone operation which makes it independent of a computer for signal processing and visual stimuli presentation. Preliminary results obtained from experiments exploring alpha rhythms and steady state visual evoked potentials attest the overall functionality and robustness of the system.

1 INTRODUCTION

EEG portable devices are mainly used for long term signal recording or for remote real-time monitoring (Jiang and Wang, 2005). They are usually small sized and low-cost and therefore suitable for a daily using. EEG-based BCI systems are however almost always dependent of a personal computer (PC) and its screen. This is mostly because they rely on real-time heavy processing algorithms and because a computer screen is needed to provide visual feedback information or visual stimuli presentation.

Current main non-invasive BCI systems based on EEG data are divided in three main classes according to the type of neuromechanisms: event related synchronization and desynchronization (ERD/ERS) of μ and β rhythms usually associated with motor imagery (Pfurtscheller et al., 1998), P300 evoked potentials (Donchin et al., 2000), and finally, steady-state visual evoked potentials (SSVEP) (Gao et al., 2003). The first approach is usually used for 1D or 2D cursor control on a computer screen to select targets or letters (as a spelling device), or for playing simple games. The large number of required EEG channels and the heavy processing needed for EEG pre-processing, feature extraction and classification make this BCI approach highly dependent on a computer system. The visual P300-based BCI approach depends on the user attentional focus to an infrequent specific visual stim-

ulus that occurs among other random stimuli (Pires et al., 2008). The stimuli can be generated with LEDs or with a low cost display controlled by a microcontroller, without resorting to a computer and screen. Assuming that many EEG epochs are averaged, then low computational demanding feature extraction techniques can be implemented on a microcontroller or DSP. However, the use of a large number of epochs slows down the BCI transfer rate and it requires a buffer of several seconds. In the last BCI approach, the SSVEP results from a stimulus flickering at a constant frequency. The flicker stimuli are easily implemented with some LEDs, and signal feature extraction and classification can rely essentially on a FFT (fast fourier transform) that can be computed on a simple DSP.

Therefore, the SSVEP BCI approach is the only one that can be easily implemented on a stand-alone device. Some works have already been developed following a similar approach. The work presented in (Gao et al., 2003) describes a stand-alone device DSP-based. A 48 LED stimuli generator is used to control external devices (TV, videos, etc.) through the classification of SSVEP signals recorded at the occipital brain region. The LEDs are flickering at frequencies between 6 and 15 Hz with a 0.2 Hz resolution.

The use of a stand-alone device is of particular importance for us since it is intended to be applied as a BCI to steer a wheelchair (Pires and Nunes,

2002). Therefore, computer independence, portability and low power consumption are required criteria. BCIs based on SSVEP are not considered true BCIs because the users have to gaze the specific stimulus and therefore have to move the eyes. Notwithstanding this, the interface can be suitable for people with severe motor disabilities and unable to control standard interfaces such as joysticks, head switches, voice or eye trackers, but still able to perform small eye movements.

The remaining sections of the paper describe the design and implementation of the system still under development, and also some preliminary results already reached.

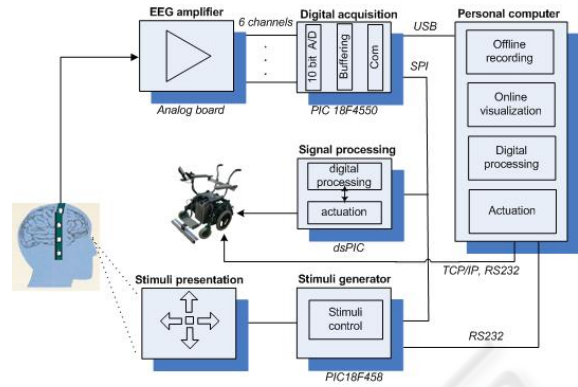


Figure 1: System architecture.

2 MODULE ARCHITECTURE

The diagram on Figure 1 illustrates the proposed architecture. The first module is a 6 channel EEG amplifier that receives EEG signal picked from non-invasive electrodes. The output signal is in the range of 0 – 5V. The data acquisition module is a PIC 18F4550 (Microchip, 2008), which was configured to sample the signal at a 512 Hz rate and was implemented based on a real-time interrupt. The A/D converter has a 10 bit resolution. The digital signal is then sent via USB to a PC for data recording, monitoring or real-time signal processing. If working on stand-alone mode, digital data is sent via SPI to the dsPIC 30F3013. The dsPIC is able to perform some statistical computation, digital filtering and FFT computation to extract signal features for classification. The output from decoded patterns can be directly sent to a control unit on the wheelchair. The last module is a stimuli generator implemented on the PIC 18F458. It controls a set of LEDs that can be activated sequentially, randomly, or at a given frequency (Figure 5). The module is therefore suitable to generate stimuli for SSVEP and for P300. In the case of P300 operation, each stimulus code is sent to the dsPIC via SPI or to the PC via USB or RS232. Table 1 presents some of the main specifications of the system.

On the present development stage, only one amplifier channel was implemented. The signal processing algorithms are not running at the dsPIC, but only at the PC after signal recording.

2.1 Amplifier

EEG signals are characterized by having very low amplitude values, typically in the range of 5-100 μ V, requiring a very accurate conditioning in order to amplify input signals and reject the existing noise or in-

Table 1: Overall system specifications.

Number of channels	6
Resolution	10 bit
Min input voltage step detect	195nV
Input voltage full scale	200 μ V
Input frequency range	0.25-45 Hz
CMRR	100-120 dB
Noise spectral density	339 nV/ $\sqrt{(Hz)}$
Min and Max Gain	66-91 dB
Current per channel	6 mA

terferences. A high input impedance of the conditioning module avoid signal distortion due to loading effects.

An EEG amplifier module was developed for signal conditioning and amplification. The module design follows the OpenEEG project approach (OpenEEG-Project, 2008). The main difference was the insertion of a notch filter to reject the 50 Hz from power line interference. This improvement made possible the use of standard electrodes, whilst the OpenEEG project needs non-standard shielded electrodes.

The amplifier module is shown in Figure 2. The EEG signals acquired from the electrodes pass through the protection circuit who acts as a voltage and current limiter. The instrumentation amplifier with 28dB of gain is implemented with the INA128P circuit that is characterized by having low offset voltage, typically 50 μ V, and high Common Mode Rejection Ratio (CMRR) (between 100-120 dB). One second-order high-pass filter with cut-off frequency at 0.16 Hz and gain 15 to 40dB follows the INA128P in order to increase the input signal amplitude and to reject the DC component imposed by the amplifier offset voltage. Then, the signal passes through an anti-aliasing filter that is a third-order Bessel low-pass filter with cut-off frequency of 45Hz and gain 22.4dB. In order to reject the 50Hz component, the

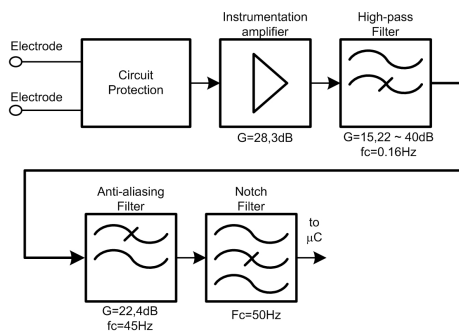


Figure 2: Block diagram of EEG Amplifier.

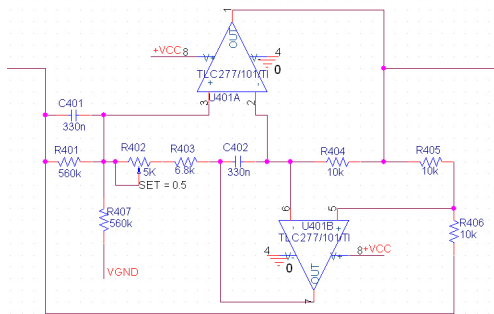


Figure 3: Notch filter circuit.

EEG amplifier stage includes one notch filter implemented using the GIC (Generalized Immittance Converter) topology with adjustable central frequency, f_0 , varying between 44Hz and 58Hz and 50dB of attenuation at f_0 . The notch filter circuit implementation and EEG amplifier frequency response simulation are shown in Figures 3 and 4. The signal conditioning system has a noise spectral density of $339nV / \sqrt{Hz}$, which achieves a signal-to-noise ratio higher than the maximum required by the A/D converter of 61.96 dB for a $N = 10$ bit converter (Eq. 1).

$$SNR = 6.02N + 1.76dB \quad (1)$$

The circuit dynamic range has to take into account the signal dynamics of a crest factor of about 6dB plus the required SNR of the ADC. Therefore the required circuit minimum dynamic range is 67.96dB. The circuit SNR, considering a noise bandwidth of 256 Hz is about 120dB which is more than enough for the application. The sampling frequency of the ADC was set to 512Hz that is a decade above the aliasing filter cut off frequency. The filter attenuation at half the sampling frequency is not critical since the type of signal detected by the sensor do not fall in this frequency zone.

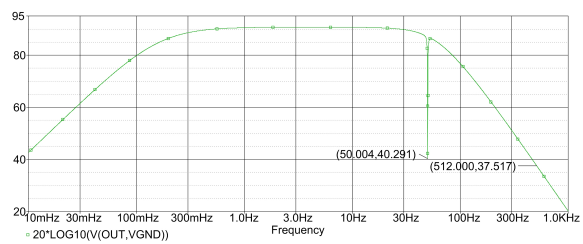


Figure 4: Amplifier gain obtained from PSPICE simulation.

3 EXPERIMENTS AND RESULTS

Two experiments were performed with two subjects to evaluate the performance of the system. The EEG activity was recorded from Ag/Cl electrodes at position Oz according to the international 10-20 standard system (Figure 5). The electrode was referenced to the right mastoid and the ground was placed at AFz. The cap and electrodes are g.tec products.

The first experiment consisted on the analysis of the alpha rhythms (typically in the range 8-12 Hz). It is known that there is an increase of the amplitude of alpha rhythms when the eyes are closed and a decrease when the eyes are open (Feige et al., 2005). Figure 6 (top) presents the recorded signal, bandpass filtered between 8 and 12 Hz, during the two situations. It was asked the user to be relaxed and to close the eyes and open them (without any kind of visual stimuli in front) alternately during some seconds. During the open-eyes period there is a clear decrease of alpha amplitude, and an increase during the closed-eyes period. In Figure 6 (bottom), the FFT of the non-filtered recorded signal shows a peak at the 10 Hz when the eyes are closed. To compare and evaluate the results, similar experiments were performed with a certified commercial amplifier, reaching the same results.

The second experiment was performed to validate simultaneously the stimuli generator and the SSVEP BCI approach. The user was asked to gaze alternately two LEDs stimuli blinking at frequencies 15 Hz and 16 Hz. Figure 7 shows the SSVEP signals recorded at Oz channel. The two frequencies were clearly discriminated. The plot corresponds to the application of the FFT to a time window of 1 s (1 Hz resolution). These results attest the validity of the overall system and also of the SSVEP BCI approach.

4 CONCLUSIONS

This paper describes the implementation of a low cost EEG system for BCI. The amplifier, digital data ac-

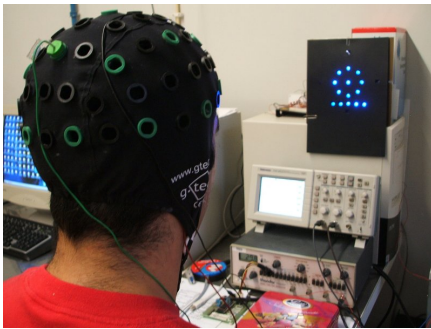


Figure 5: Subject with electrodes cap and stimuli presentation.

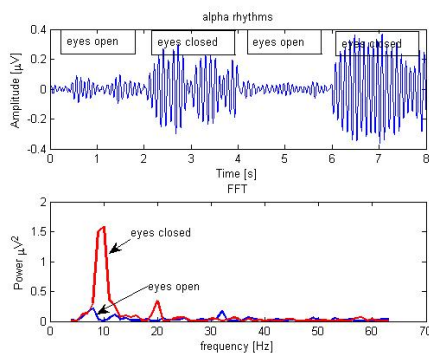


Figure 6: Top) Alpha rhythms recorded with open eyes vs. close eyes; Bottom) FFT of recorded signal with open eyes vs. close eyes.

quisition and USB communications were already implemented, tested, and validated. A full stand-alone operation was already achieved, through the connection of the dsPIC via SPI, even though signal processing algorithms are still in the early steps of development. Also, the batteries supply system is currently under development. The proposed SSVEP BCI was also tested reaching 15 and 16 Hz discrimination applying a FFT. For comparing purposes the experiments were also performed with a commercial EEG system. The results showed a similar performance.

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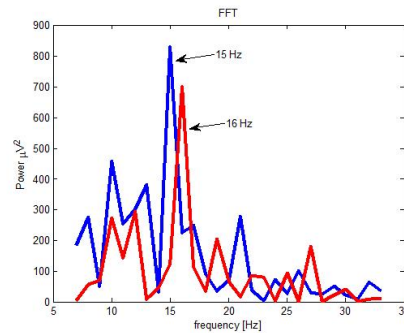


Figure 7: FFT of the SSVEP signal for a 15 Hz and 16 Hz stimuli.

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