

Multiple Biopotentials Acquisition System for Wearable Applications

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Abstract: Wearable devices for monitoring vital signs such as heart-rate, respiratory rate and blood pressure are demonstrating to have an increasing role in improving quality of life and in allowing prevention for chronic cardiac diseases. However, the design of a wearable system without reference to ground potential requires multi-level strategies to remove noise caused from power lines. This paper describes a bio-potential acquisition embedded system designed with an innovative analog front-end, showing the performance in EEG and ECG applications and the comparison between different noise reduction algorithms. We demonstrate that the proposed system is able to acquire bio-potentials with a signal quality equivalent to state-of-the-art bench-top biomedical devices and can be therefore used for monitoring purpose, with the advantages of a low-cost low-power wearable devices.

1 INTRODUCTION

Every year in EU and US over 4 million deaths are caused by cardiac diseases. More than 100 millions of people conduct their life after a heart attack and there are 30 million of people suffering from arrhythmia and other cardiac and cardiovascular disorders (WHF, 2012). On the other hand, there are more than 1 Billion people suffering from neurological diseases, even if the international community was seriously underestimating in traditional epidemiological and health statistical methods its effects. The health cost for treatments associated with these diseases is about 450.5 B\$ per year (WHO, 2012).

The monitoring of hearth rate, blood pressure, oxygen saturation, brain activity and other physiological parameters can help minimize this cost and enhance the quality of life for a significant part of the world's population. During hospitalization, monitoring these parameters is relatively simple and can be obtained with high-end bench-top diagnostic systems. To extend the control and the diagnostic capabilities out of hospitals it is necessary to provide unobtrusive and low cost systems, which should be equipped with adequate sensor interfaces, sufficient computational resources and with optimized power management strategies.

One open challenge in this field is the design of unobtrusive systems that can be used in different applications of human biosignal analysis. Their goal is to be able to run the needed algorithms for monitoring and diagnosing the life parameters, while providing adequate communication interfaces and a prolonged battery life. The design of a wearable system for biosignal monitoring presents many challenges, since it involves integrated circuit design, mixed analog-digital signal acquisition techniques, digital signal processing, low power algorithms and adaptive filtering techniques.

Given the nature of the signals to be acquired, which lie in the 1 μ V - 10 mV range, with a frequency band of 0 – 1 kHz, analog acquisition and robustness to noise is crucial. Noise interference is caused by the floating reference potential of the human body and by the 50/60 Hz power-line interference (PLI). To achieve a robust design of a wearable system for biosignal measurement, we need to properly address the minimization of noise sources.

In this paper, we present a wearable platform based on a low power Cortex M4 microcontroller and a high performance Analog Front End (AFE) (Schonle et al., 2013). The AFE is equipped with a scalable SPI-interface, allowing accurate acquisition of bio-potentials. The computing performance of

the microcontroller allows advanced signal processing to filter the noise and apply processing techniques to achieve robust biosignal monitoring.

This work demonstrates the performance of our platform with two kinds of vital signs: the acquisition of an Electrocardiogram (ECG), based on a 3 leads configuration, and of an Electroencephalogram (EEG), using 2 fully differential channels. We implemented, profiled and compared four approaches for the PLI noise filtering. Furthermore, we show the performance of the acquisition system and we compare the results with a commercial state-of-the-art AFE (AD7194) for the ECG and a non-portable hospital device for multichannel bio-potential acquisition for the EEG.

ECG data acquired with our system and with the AD7194 chip exhibit similar characteristics, having a signal-to-noise ratio (SNR) of 13.4 dB in our case and 12.3 dB for the AD7194. By applying PLI filtering techniques we were able to improve the performance of our system and to achieve a SNR of up to 30 dB. The acquired EEG data was instead compared against a state-of-the-art non-portable device, used in clinical environments. We verified that data acquired by the two systems has the same temporal evolution and frequency spectrum.

The remainder of the paper is organized as follows: Section 2 introduces related works; Section 3 illustrates the system setup and the nature of the signals we are considering, while Section 4 describes the processing techniques applied. Section 5 presents experimental results. Finally, in Section 6 we draw the conclusions and discuss some future developments.

2 RELATED WORKS

In recent years, there have been numerous research and commercial efforts in the design of wearable biopotentials measurement systems. There are already several low-cost devices on the market, like the ones from OMRON (Omron R7, 2004), Philips (Philips MX40, 2011) and VIVAGO (Vivago 8005, 2012). All these devices offer limited computational resources and are not designed for applications requiring flexibility e.g. in terms of multi-modality or number of channels. Their counterparts is represented by novel wireless portable and quite compact systems, such as the g.MOBIIlab+ by G.TEC (GTEC g.MOBIIlab,), which at one side are more flexible, enabling multi-modal multi-channel biosignal recording, however being expensive and often requiring the use of proprietary software.

At research level, physiological signals monitor-

ing systems have appeared since the MITHrill2003 prototype (DeVaul et al., 2003), which represents a milestone in wearable computing platforms. It is based on a PDA connected with a sensor board for biopotential acquisition. The embedded sensor board is equipped with a 3-axes accelerometer, temperature sensor and an analog front-end for EMG-ECG acquisition. Sampled data is transmitted from the sensor board to the PDA for processing. Another important similar project is the AMON platform (Anliker et al., 2004), a monitoring system composed by a wrist-worn device capable of measuring blood pressure, O_2 saturation, ECG and body temperature, which sends acquired data to a base station for remote storage, processing and support functionalities. Furthermore, there is a 2-axis accelerometer to correlate vital parameters to user activity. The project (Mundt et al., 2005) proposes a system to measure and collect biological data for up to 9 hours in extreme environments. The board is based on a PIC microcontroller and can collect ECG, heart rate, blood pressure and saturation, body temperature and movements. The user can interact with the acquisition system using a PDA, thus obtaining an unobtrusive system. However, the main limitation of all these architectures is the need to transmit data from sensors to a PDA or a base station. The sensor nodes are not equipped with sufficient computational resources, thus the data transmission limits the bandwidth of the processed signals and has a significant impact on power consumption. The recent advances in embedded system integration enable on-board signal processing required to improve the quality of the signals and possibly to perform part of the signal processing, thus opening the possibility to optimize the power consumption. These are the opportunities we want to exploit in this work.

A wireless system performing on-board processing is presented in (Buxi et al., 2012). The system is equipped with a custom DSP and a TI MSP430 microcontroller. The DSP is used to perform Independent Component Analysis (ICA) and adaptive filtering to detect heart rates and cardiac arrhythmia. Although the system is well optimized for low power operation, it is based on a custom DSP independent from the low power commercial microcontroller, therefore limiting scalability in more complex and diverse applications. (Penders et al., 2011) presents a neck-band system for cardiac activity monitoring, which implements a CWT based BPM algorithm and an ECG derived respiration rate monitor. The data can be stored in an SD card or transmitted by a low power radio. The digital platform is an MSP430 and the ASIC analog front end offers great performance in terms of power con-

sumption ($21\mu\text{V}$), but it is connected to the microcontroller with an analog interface. An analog back-end interface can be affected by additional noise and reduces the system scalability, when compared to digital interfaces. Recently, wearable systems started also to cope with EEG signal acquisition and monitoring. Several wireless and portable EEG monitoring systems have been published so far in literature. Some implementations exploit discrete components (Sullivan et al., 2008) and (Chen and Wang, 2011), while others rely on fully integrated systems, especially for the implementation of low-noise analog front-end circuitries. An example of a fully implemented wireless EEG sensor node is presented in (Brown et al., 2010) which uses the analog front-end published in (Yazicioglu et al., 2008). All these systems are strongly oriented to a single application scenario therefore lacking in flexibility. Furthermore, they cannot be used in applications requiring multimodality, where data fusion from heterogeneous sensors is required.

The lesson learned by these inspiring approaches is that we must join the design of a high performance AFE to allow the acquisition of the principal biopotentials (EEG, ECG and EMG) with an efficient microcontroller with integrated DSP functions. The AFE must have a digital back-end with SPI or I2C to provide a faster communication with the microcontroller, which must have sufficient computational resources to locally execute algorithms for filtering and information extraction, without data transmissions to a base station.

3 SYSTEM DESCRIPTION

3.1 System Architecture

The Cerebro wearable device is a smart sensor node designed for medical and fitness applications and its high-level functional block diagram is shown in Fig. 1. This node consists basically of a multichannel analog-front-end (AFE) with a digital interface. The AFE is called Cerebro ASIC (Schonle et al., 2013), which is responsible for the biomedical signal acquisition. An ARM microcontroller with a FPU DSP instruction set is used for noise filtering and further feature extraction. Additional inertial and pressure sensors have been added in order to collect data on the patients' motor activity. After biomedical signals have been acquired and elaborated, they can be locally stored on a SD card or wirelessly transmitted by a Bluetooth module to a nearby smart phone or tablet.

The supply of the system is handled by a dedicated IC equipped with an internal switching voltage

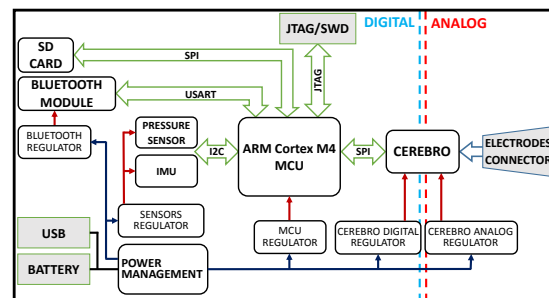


Figure 1: Overview of the Cerebro wearable device.

regulator. This power management circuitry automatically detects the power source in use (battery or USB connector) and manages the recharging of the battery while providing low-dropout voltage regulators to the inertial and pressure sensors as well as to the Bluetooth module. This flexible solution for controlling the power management allows us to switch-off submodules of the board that are not required for a targeted biomedical application and thus enhancing battery lifetime.

The board is designed on a 6 layers printed-circuit-board (PCB) with a single ground plane, a split power plane (between analog and digital) and 2 signal layers (top and bottom). Discrete components are placed on both top and bottom layers in order to further reduce the resulting board size, which is $85 \times 50\text{mm}$.

The Cerebro AFE has already been tested with ECG signals (Schonle et al., 2013) and for the recognition of hand gestures using EMG signals for prosthesis control in (Benatti et al., 2014). In this work, we aim at a more general scenario where the developed platform can be used in a large variety of different biomedical applications including EMG, ECG and EEG signal acquisition, or combinations of them. We further analyze the nature and requirements of ECG and EEG signals, which are used to prove the capabilities of the biomedical platform.

3.2 ECG Signal

The ECG signal is one of the most important biosignals that can provide a great amount of information in medical and fitness applications. It senses the electrical activity of the heart during its muscular contractions. During the heartbeat, the muscular cells on the hearth surface depolarize their membrane. The resulting potential differences can be detected using surface electrodes placed in a proper configuration and a low noise signal amplifier. The typical frequencies of ECG signals go from 0.01 to 250Hz and the amplitude is lower than 5 mV.

As all the biosignals, the ECG is difficult to manage because it is a low amplitude signal affected by different sources of noise (e.g. power line interference, baseline wander, ground loop noise, muscular contraction and respiration artifacts). For these reasons, in the design of an ECG signal detection system and, in general, for the design of a wearable device for biopotentials measurement, the system level hardware and software design is extremely important.

3.3 EEG Signal

EEG represents a collection of electrical voltages recorded at different locations on the scalp of patients. Electrical characteristics of these signals show a typical bandwidth range from 0.5 to 100 Hz with a peak amplitude of about 100 μ V. Such signals are generated by millions of underlying neurons that fire asynchronously and are responsible for the brain activity. Hence, the EEG recording does not contain the activity of single neurons but the averaged activity of millions of neurons. For this reason, raw (unprocessed) EEG signals do not show any kind of regularity in the time-domain. However, after proper band-pass filtering of the EEG signals, e.g. extracting delta, theta, alpha and beta frequency bands, more regular patterns can be identified, especially in the lower frequency bands. These filtered EEG bands are of high interest because they are strictly correlated with the states in the brain such as wakefulness, sleep, or even with some severe diseases including epilepsy and neoplasms (Moore and Lopes, 1998), (Buzaki, 2006) and (Nunez and Srinivasan, 2006).

EEG evaluation is thus an important tool to learn about brain functioning. The understanding of brain functions, however, is currently limited to clinical environments and may not accurately reflect brain activities in the real world. Furthermore, long recordings are feasible only during sleep as the EEG amplifiers are large, inconvenient for patients, heavy, and need to be plugged in, making it unable for patients to move more than a few meters.

On the contrary, a wearable EEG device is not restricted to these limitations, exploiting paradigms of integration, low power operation, and small device size (Casson et al., 2010). This increased degree of freedom for the wearable EEG device allows to record biological signals also outside of the clinical laboratory, increases the interests in the research field that is currently restricted to medical use cases. Such a portable device has countless applications with high market potential, ranging from early detection of diseases to the monitoring of well-being habits and cognitive behavior.

To provide a satisfactory wearable EEG device, it is essential to build it such that its performance is comparable to those obtained in the state-of-the-art clinical devices. We therefore compare our system with the commonly used bench-top clinical device. It is shown that we obtain similar performance in field tests.

3.4 Data Processing

All applications relying on the acquisition of biopotential signals share the common need to reduce noise and interferences by digital post-processing. The most common sources of interference are: power-line interference (PLI), baseline wander (drift), movement and breathing artefacts, changes in the electrode impedance and intra-channel interference. In particular, PLI introduces a 50/60 Hz sine interference to the signal. It is always noticeable, even when the system is battery-powered (Serrano, 2003), that its accurate removal is a critical but required task.

Different approaches have been presented in literature so far for the removal of PLI. The simplest approach is a notch filter, which is a stop-band filter that allows to attenuate the frequency of a narrow band. The rejected band depends on the quality factor Q of the filter: with a $Q = 50$ the notch filter provides 10 dB attenuation at the frequency $f_{pli} \pm 0.5$ Hz. This approach has the advantage to be easily implemented and to have low computational requirements, but it introduces distortion in the signal power spectrum.

More advanced approaches have been developed in literature to overcome the limitations of the notch filter and to accurately separate the PLI from the EEG signal. In particular, there are methods based on time-domain subtraction (Levkov et al., 2005), regression subtraction (Bazhyna et al., 2003) and sinusoidal modeling (Zivanovic and González-Izal, 2013). These methods all share the basic approach, which consists in the estimation of the sinusoidal interference and its removal from the acquired signal. Brief summaries of these technique is listed below.

The time-domain subtraction method first divides the signal in linear and non-linear segments which is performed by setting a threshold on the second derivate of the signal. Then, in the linear segments, the signal is averaged and the PLI is estimated, which is then also removed from non-linear segments.

Regression-subtraction or time-correlated power-line interference subtraction estimates the amplitude and phase of the PLI and then subtracts it from subsequent samples. This approach models the interference as two quadrature sinusoids with the same frequency and uses blocks of data to estimate it with a

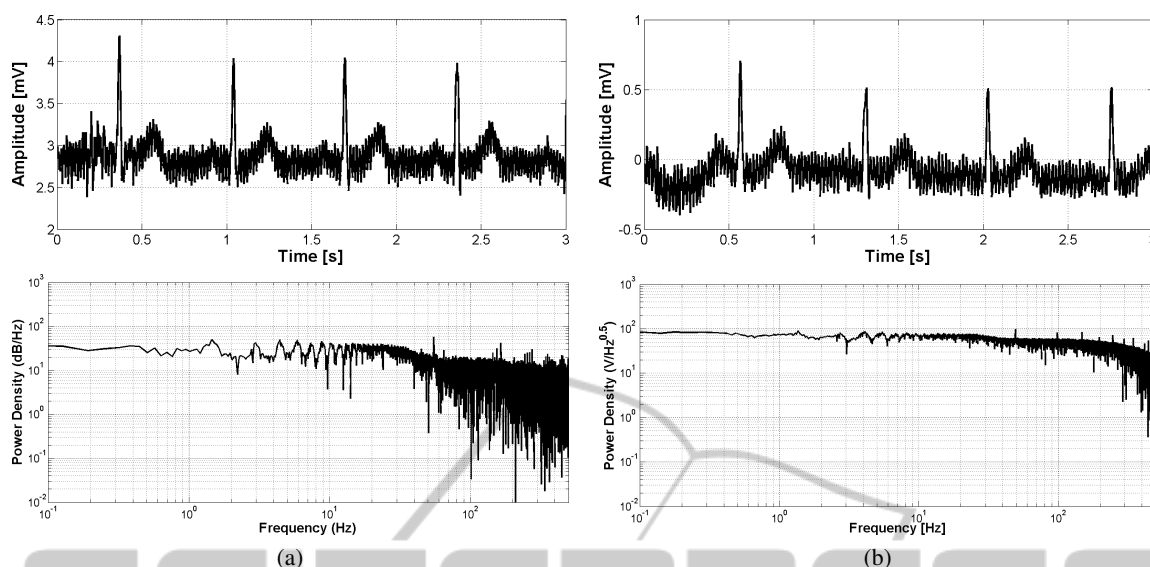


Figure 2: Raw ECG signals (top) and their FFTs (bottom) for the Cerebro platform (a) and for the AD7194 acquisition board (b).

least-squares fit.

The sinusoidal modeling approach models the interference by a set of harmonically related sinusoids modulated by low order time polynomials. The polynomial coefficients can be estimated by minimizing the quadratic error between the signal and the model in a given interval. Then the estimated PLI is subtracted from the original signal to obtain a noise free signal.

Time domain method relies on the separation of linear and non-linear segments, which is easily applicable to ECG signals, but is not useful in other cases. Regression-subtraction and sinusoidal modeling, on the other hand, use short intervals of signals (0.5 – 1.5s) to estimate the sinusoidal source, which is then effectively removed from the original signals, preserving their other characteristics.

4 EXPERIMENTAL RESULTS

4.1 ECG Signal Acquisition

To test the capabilities of our system and to compare the different de-noising approaches, we used a 3-lead ECG acquisition scenario. In this set-up, we used one differential channel of the AFE to acquire the ECG signal. We placed two disposable electrodes on the wrists of the user and an additional electrode was placed on the ankle as the reference potential (patient ground).

The ECG signal was acquired with our platform and with a reference state-of-the-art AFE, which is the

Analog Devices AD7194 chip. We used the development board provided for this chip, which is equipped with 8 analog channels and can be connected to a PC via USB for the data acquisition. Our device sent the sampled data to a PC via Bluetooth and all the collected data was stored and processed on the PC. The two systems have been configured in the most similar way possible, setting the acquisition frequency at 1 kHz and the gain at 8 for our device, while the ADC was set to sample at 960 Hz with a gain of 128.

The signals acquired from the two devices are plotted in Fig. 2, along with their frequency spectrums. From the plots we can observe that the two systems provide signals of comparable quality. The frequency spectrum of the two acquired signals is very similar. The Cerebro ASIC acquired signal exhibits a strong PLI component at 50 Hz (the exact measured frequency of the PLI was 55 Hz). The ADC has an internal filter, which reduces the PLI contribution. Using the data acquired with Cerebro, we implemented and compared the PLI filtering techniques described in the previous Section. Ideally, the perfect filtering technique should remove the PLI component and leave the rest of the signal frequency spectrum as it is.

The result of the PLI removal for the considered approaches is shown in Fig. 3, where we plotted the frequency spectrum for the raw and the filtered signals acquired with our system. From the plots we can see that all the considered algorithms remove the PLI component, but they alter the rest of the frequency spectrum in different ways. We can note that the notch filter removes also frequency components close to the PLI, while the time-domain approach alters consider-

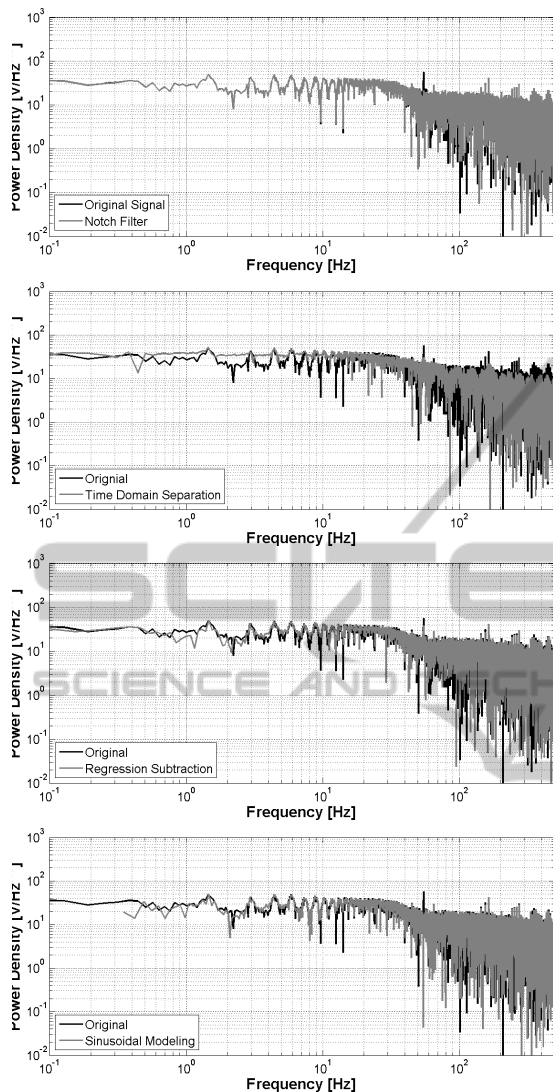


Figure 3: Comparison of the FFT of the PLI filtering techniques (top to bottom): notch filter, time domain subtraction, regression subtraction and sinusoidal modeling.

ably the spectrum of the output signal, for both lower and higher frequencies.

The regression-subtraction method is the one that alters less the frequency spectrum of the signal, only reducing the PLI component. Also the sinusoidal modeling approach is very precise and removes correctly the PLI without additional changes in the signal. It is worth noting that the signals also present interferences at frequencies multiple of the main PLI component (e.g. 100 Hz), which can be removed applying the considered approaches also for those frequencies.

To summarize the results of this comparison, we computed the SNR of the filtered signals, obtaining 21.9 dB for the notch filter, 28.3 dB for the

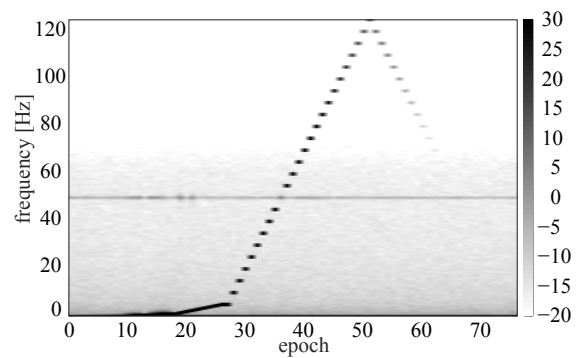


Figure 4: Color-coded power spectra of consecutive 90-s epochs (4 s window) with Hanning window. Data was sampled with 250 Hz. Spectra are color coded on a logarithmic scale, 30 dB corresponds to an input signal with an amplitude of $100\mu\text{V}$.

time-domain subtraction, 29.5 dB for the regression-subtraction and 30.4 dB for the sinusoidal modeling approach. The latter two methods deliver considerably better signal quality and are the ones chosen to be used in our system. In particular, the regression subtraction method has been implemented and used for the final ECG and EEG applications, since it is the one that preserves better the frequency response of the system.

4.2 EEG Signal Acquisition

A spectrogram is shown in Fig. 4, which gives a better insight on the overall performance of the wearable EEG device. The color map on the right hand-side has the dimension decibel and indicates the power of the recorded signal. A $100\mu\text{V}$ sinusoidal signal is sampled with the device at a sampling frequency of 250 Hz while the input sinusoidal signal frequency is increased over time from 0 to 250 Hz. Each EEG channel of the device is low-pass filtered at a cut-off frequency of 66 Hz. The dots on the illustration represents the sinusoidal amplitude changes (from grey to white) indicating the signal attenuation by the low-pass filter. The spectrogram also shows signals aliased back in the Nyquist band which were generated by feeding the EEG device with sinusoidal signals with frequencies higher than half of the sampling frequency. The horizontal gray line at 50 Hz is the residual of the mains interference being successfully suppressed to a certain degree and does not significantly disturb the EEG signal. This spectrogram illustrates that the Cerebro AFE is well-suited to record EEG signals with amplitudes below $100\mu\text{V}$. In the frequency band of interest, i.e., from 0.5 to 100 Hz, a signal-to-noise ratio of more than 35 dB is observed.

In order to provide a useful wearable EEG device,

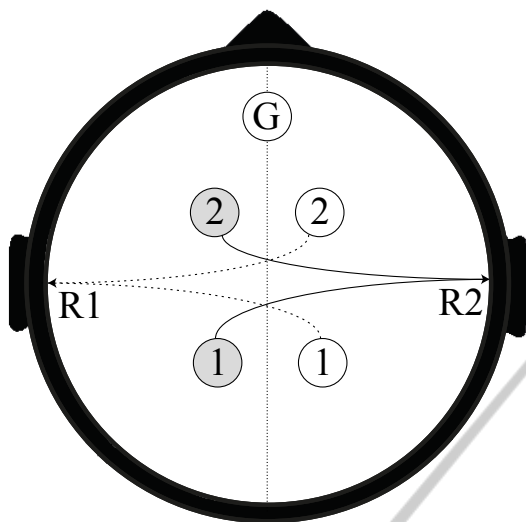


Figure 5: Illustration of the electrodes arrangement on the head of the patient with the denoted patient ground G. The pairs of electrodes are split in colors where the gray ones are referenced to the right ear (R2) and the the white ones to the left ear (R1).

it is essential to build it such that its performance is comparable to those obtained in the state-of-the-art in clinical use. For this reason, a direct comparison with the commonly used state-of-the-art device in hospitals is performed in this paper to show that the wearable EEG device achieves similar performance.

The specification of the wearable EEG device is performed taking the recorded EEG signals from both devices, i.e., our wearable EEG device with limited hardware resources and the state-of-the-art recording device in operation at the University Hospital of Zurich (USZ) which has no limitations in power consumption and hardware resources. The EEG signals are simultaneously acquired from the same patient at a sampling frequency of 250 Hz with the wearable EEG device and at 256 Hz with the USZ device.

Fig. 5 illustrates the placement of electrodes on the scalp of the patient. During the recording, a test subject is connected to different EEG channels, where two out of four channels are connected to the wearable EEG device (numbered gray electrodes), while the remaining two are connected to the state-of-the-art device used in USZ (numbered white electrodes). The pairs of electrodes connected to both devices are placed next to each other in order to record EEG signals from the common source.

The current measurement setup in use at USZ consists of polygraphic amplifiers provided by Artisan (Micromed, Mogliano Veneto, Italy) and the recording is performed using the Rembrandt Datalab (Embla System, Broomfield, CO, USA). Before analog-to-

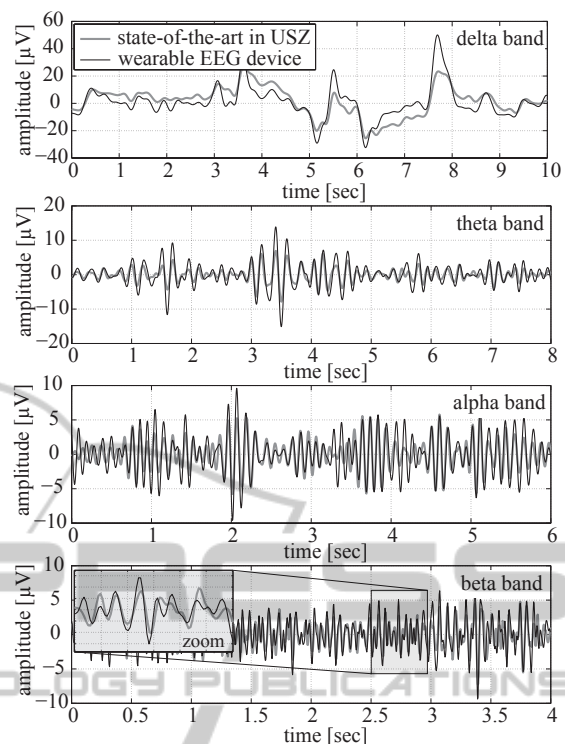


Figure 6: First pair of EEG channels comparing the wearable EEG device with the state-of-the-art in USZ. Brain waves are obtained after proper filtering and decomposing of the EEG signals in delta, theta, alpha, and beta frequency bands.

digital quantization is done, the analog EEG signals are high-pass (-3 dB at 0.16 Hz) and low-pass filtered (-3 dB at 67.2 Hz), as indicated in (Moore and Lopes, 1998).

In the wearable EEG device, the analog front-end (Schonle et al., 2013) samples the analog signals at 250 Hz. After the analog-to-digital quantization, digital high-pass (-3 dB at 0.16 Hz) and low-pass filtering (-3 dB at 66 Hz) is performed on the digitized signals.

After acquiring the EEG signals from the two acquisition systems, a post-processing filter has been applied in order to highlight major cerebral waves of the patient. As illustrated in Fig. 6, the EEG Channel-1 of both devices deliver similar EEG signal patterns for the different EEG bands of interest (Channel-2 shows very similar behaviour, not shown). For both devices, waves are obtained according to the following scheme: delta low-pass filter at 4 Hz, theta band-pass filter between 4 and 7 Hz, alpha band-pass filter between 7 and 15 Hz while beta is band-pass filter between 15 to 30 Hz.

FFT plots of the two acquired channels are shown in Fig. 7, which provides a different perspective of the measured EEG. Frequency responses of both devices overlap over the whole Nyquist frequency band. The

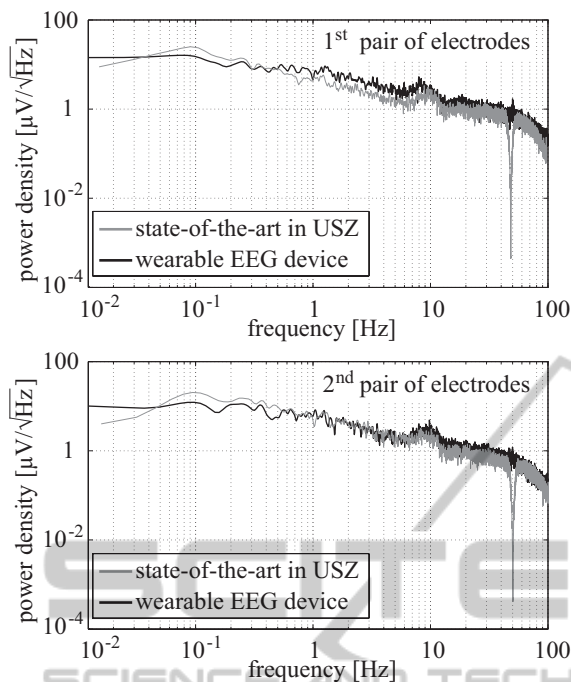


Figure 7: Frequency response of the two electrode pairs. FFTs are very similar in amplitude except for the notch filter at 50 Hz of the USZ acquisition system.

only noticeable difference is that the USZ device uses a notch filter to cancel mains interference while the wearable EEG device handle this problem by applying the regression subtraction approach and subtracting the estimated interference signals (Schonle et al., 2013).

5 CONCLUSION

In this paper, we presented the design and evaluation of a wearable node able to acquire heterogeneous vital signs and having on-board filtering and processing capabilities. In particular, we considered the acquisition of EEG and ECG signals, comparing our system with state-of-the-art solutions. We also described the implementation and the results of different denoising algorithms that can be executed in real-time with our platform. We demonstrated that the output of the Cerebro node for EEG and ECG signal filters accurately the power-line noise reaching a SNR of 30dB, which is comparable with state-of-the-art devices, while represents a much less expensive solution.

Furthermore, Cerebro offers higher scalability w.r.t. comparable commercial devices or other research prototypes and higher flexibility in terms of multi-modality. Therefore, we think that the proposed

wearable platform has high potential to be used not only for the monitoring of vital signs, but also for biomedical real-time signal processing. The Bluetooth interface allows to connect the Cerebro board to mobile devices paving the way to the development of efficient user interfaces for clinician and patients. Future work will explore the use of Cerebro out of the lab, exploiting the scalability of the system and challenging the ability to perform complex algorithms on-board.

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