A PLATFORM FOR JOINT ANALYSYS OF BIOSIGNALS ENSEMBLES IN REAL-TIME USING FPGA

PLATFORMA DO ANALIZY CAŁOŚCI BIOSGLAŁÓW ZA POMOCĄ FPGA

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ABSTRACT

We present the design of a platform for acquisition and digital processing of biosignals. The objective of this platform is to process biosignals in real-time to obtain quantitative indicators for joint analysis of biosignals ensembles. An important indicator of non-linear dependence between signals is the mutual information. The estimation of the mutual information between signals is time- and resource-consuming when using standard software implementations on normal computers. To circumvent the calculation limitations on standard software implementations we use a reconfigurable computing unit of type FPGA, were the calculation of mutual information is specified in hardware.

Keywords: biosignals, joint analysis, mutual information, DSP, FPGA

STRESZCZENIE

Przedstawiamy projekt platformy służącej do pozyskiwania i cyfrowej obróbki biosygnałów. Jej zadaniem jest przetwarzanie biosygnałów w czasie rzeczywistym w celu uzyskania wskaźników ilościowych dla zintegrowanej analizy zespółów biosygnałów. Ważnym wskaźnikiem nieliniowej zależności pomiędzy sygnałami jest informacja wzajemna. Jej oszacowanie pomiędzy sygnałami przy użyciu standardowego oprogramowania na zwykłych komputerach jest mało wydajne i czasochłonne. Aby obejść ograniczenia narzucone przez narzędzia zwykle wykorzystywane w tym celu, zastosowano rekonfigurowalną jednostkę typu FPGA, w której obliczenia informacji wzajemnej są określone.

Słowa kluczowe: biosygnały, zintegrowana analiza, informacja wzajemna, Cyfrowe Przetwarzanie Sygnałów, FPGA (Programowalne układy cyfrowe)

1. Intorduction

Today technology and understanding of human electrical activity supports a myriad of innovative research in the field of biosignal applications. Biosignal carries information about the instantaneous change in electrical potential of a body region. When a biosignal is associated with a nervous system activity, it encodes the intermediary message that triggers a final response of the body, like extend a muscle or variate the heart rate. The importance of the analysis of these signals is clear for the study

of neurodegenerative diseases like Parkinson, or for detecting epileptic seizures; but they are also of interest in the study of some mild diseases like stress or bruxism. From another point of view, these signals can be used on advanced human-machine interface to control external elements for example: personal computers, videogames, prosthetic devices, wheelchairs and domestic applications.

Currently it is possible to construct heavily customized, precise, and smart biosignal sensors of wearable size for everyday use. Common human activities like physical exercise routines or a bike ride [1], can be studied electrically with a high level of detail, via electromyogram (EMG). Given the complex nature of the EMG signals their interpretation involves integral knowledge of the sensorimotor system, nervous system and the electrical and mechanical parameters of the musculoskeletal system. Therefore, the transduction of the whole stream of biosignals to high level information required on diagnosis; i.e. the observed health state of an individual in a specific time, is a challenging task. Signal processing in this sense is classically realized off-line. With the expert knowledge and experience of physicians and medical specialists, the datasets are translated to the diagnosis of a patient; compared with a previous state, or compared with medical evidence on population with similar health status, age, complexion, sex, and ethnicity among many other possible dependence factors.

With easy access and availability of real-time acquisition of biosignals, the next step is to process the ensemble of signals from the array of sensors and generate a resumed output of the state of the subject under study. Array of biosignals ensembles are complex because they carry generally mixed, redundant and irrelevant data in conjunction with noise. Their interpretation involves the execution of advanced algorithms on the data, to reduce data dimensions (given the redundant nature of the data array) and extract the patterns or features (as required for the target problem).

To construct devices that can acquire biosignals and (at the same time) process them, many technical problems need to be resolved: real-time acquisition is a resource-consuming activity from the raw data storage and also computational point of view. These two factors alone limit the size of wearable devices, and its energetic autonomy. The processing stage can comprise a simple noise reduction to computationally complex algorithms in the case of classification where on-line processing is generally an unfeasible option. In this case, the alternative to on-line processing is to transmit the data stream to an external computing facility for analysis. When acquiring on-line, and sending the data via a communication network, the wearable device needs to use a considerable amount of energy to transmit the datastream "as is" to the computing facility, reducing the energy autonomy of the system.

An advantage of on-line processing is that high-magnitude data storage could be not required: it is possible to discard raw data and store only relevant information processed and classified *in situ*.

In this work we present our platform for on-line digital biosignal processing, targeted to joint analysis of biosignals. The joint indicator selected as application is the mutual information between signals. The mutual information is a measure of the mutual dependence between signals and it is widely used for the analysis of nonlinear timeseries and classification algorithms. When the signals are long, or when the signal resolution is high (high frequency data acquisition), the calculation of the mutual information is time- and resource-consuming.

To calculate the mutual information on-line, we use a Field Programmable Gate Array (FPGA) device that is a reconfigurable computing chip able to outperform signal processing implementation in software for normal computers or standard DSP chips. The difference in the performance is that in the case of FPGA, the algorithms are implemented on hardware, using a hardware description language, in our case VHDL.

2. Joint analysis of biosignals ensembles

In this study we make the following distinction:

- A biosignal array is a set of biosignals of the same type, provided by different sensors. For example the EEG is generally composed of a set of electrodes strategically positioned on the upper surface of the head. The data acquisition array is composed by the measures of every site on every instant of time.
- A biosignal ensemble is a set of biosignals of different type, for example measurements of ECG and EMG of different muscles during a physical activity.

The problem of obtain a "pure" biosignal, for the generally noisy, raw acquisition data is generally well understood. Classically, the information content of EMG signals were treated as contamination in measured ECG signals [2] and vice versa for acquisition of EMG signals [3, 4, 5]. That becomes very important when muscles that are near to the heart area are evaluated.

If we consider a simple abstract model of interaction between N different signals; the mixing ensemble is given by equation (1), where a mixture function $m_i(t)$, $i \in \mathrm{N}$, $i \leq \mathrm{n}$, considers only binary, or pair-to-pair interactions.

$$\hat{x}_i(t) = g_i\left(m_i(t), \eta_i(t)\right), \quad i = 1, 2, \ldots, n \tag{1}$$

In this model, the signal $\hat{x}_i(t)$ is the observed signal, with the additional information of the rest of the signals ensemble. The observation function g_i incorporates the mixing $m_i(t)$ and the signal noise model via $\eta_i(t)$. The sum of the binary interactions composes the mixing, as is presented in equation (2).

$$m_i(t) = \sum_{j \neq i} f\left(x_i(t), x_j(t)\right), \quad i, j \in \mathrm{N}; i, j \leq n \tag{2}$$

For a two channel mixing, a diagram is presented in the figure 1.

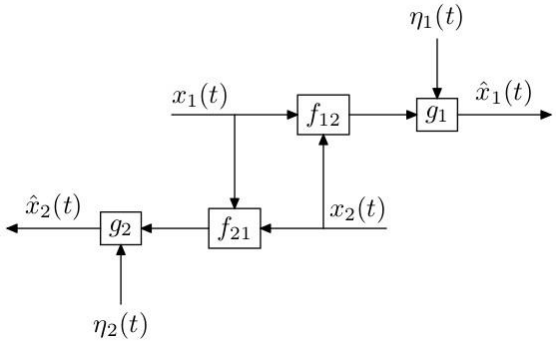

Fig. 1. A two-channel mixing signals system

The problem of recovering the original signals from the mixing is called signal separation problem and it is actively studied in the field of acoustics to separate individual voices for a mixed record. A modern method to separate biosignals is the guided underdetermined source separation (GUSSS) method [6], that is used to classify hand movements from a single EMG sensor. As an application of the GUSSS method, the same authors present a wheelchair driven by hand gestures using EMG data [7].

Figure 1 shows that the two observed signals carry information about each other and therefore, the joint study of these signals can provide insight about the behavior of the whole system. A very important measure is the quantity of information shared by the signals, or mutual information.

The mutual information for two random variables *X* and *Y* is defined as:

$$I(X,Y) = \sum_{x \in X} \sum_{y \in Y} p[x,y] \ln \frac{p[x,y]}{p[x]p[y]} \tag{3}$$

Were $p[x,y]$ is the joint probability, and $p[x]$, $p[y]$ are the marginal probabilities.

The value of the mutual information can be used as a non-linear estimation of dependence between signals. For example in an array we can identify the signals that are redundant from the signals that provide unique information.

Mutual information can be very useful to study delayed dependence between signals. For example we can calculate the mutual information between the signal $x(t)$ and the signal $y(t + \delta)$.

$$I_\delta(X,Y) = \sum_{x(t)\in X} \sum_{y(t)\in Y} p[x(t), y(t+\delta)] \ln \frac{p[x(t), y(t+\delta)]}{p[x(t)]p[y(t+\delta)]} \tag{4}$$

If we plot $I_\delta(X,Y)$ versus δ, the first minimum of the delayed mutual information can be used to identify a structural delay between signals.

We can compare, for example, the delayed mutual information of a signal with respect to itself: $I_\delta(X,X)$ versus δ In this case, the first minimum of the mutual information represent the delay of an embedded system [8], $Z \subset R^D$.

$$z(t) = \{x(t), x(t+\delta), x(t+2\delta), \ldots, x(t+(D-1)\delta\} \tag{5}$$

The equation 5, can be rewritten:

$$z(t) = \{z_k(t)\}_{k=1}^{D} \tag{6}$$

Where $z_k(t)=x(\tau_k(t))$ and the coordinate-dependent delay function $\tau_k(t)$ is defined by:

$$\tau_k(t) = t + (k-1)\delta), \quad k = 1, 2, \ldots, D \tag{7}$$

If the system is stationary in a sufficiently long time window, the existence of an attractor on the delay coordinates space represents the fact that the original signal carried information for a D-dimensional dynamical system. In this case, the study of a single variable is not justified because it will represent only a projection of the original system.

3. Platform description

The analysis of biosignals ensembles is a very important subject in medicine and rehabilitation. For example in [9], Castroflorio et al. studied the joint analysis of EMG and ECG signals for detection of sleep bruxism. The difficulty encountered during processing biosignals ensembles, is that they require sophisticated methods for detection and classification of events. The algorithms for signal processing differ in almost every application, and often the processing parameters are fine tuned to the specific characteristics of the individual under study. In the case of EMG, a survey of the common techniques for signal processing is presented in [10].

Design and development of joint analysis platforms can represent a complex task, but the satisfactory construction of online systems can help to improve the knowledge and treatment of significant diseases like Parkinson. In paper [11] the early diagnostic of Parkinson using EMG information is studied. The case of Parkinson disease is interesting because up to date satisfactory methods of early diagnosis of Parkinson are not available and current studies are focused in the combination of biosignals as a strategy for obtaining better results in diagnosis. A joint study of EMG, EEG, and voice audio signals can contribute to obtain more accurate methods of diagnosis.

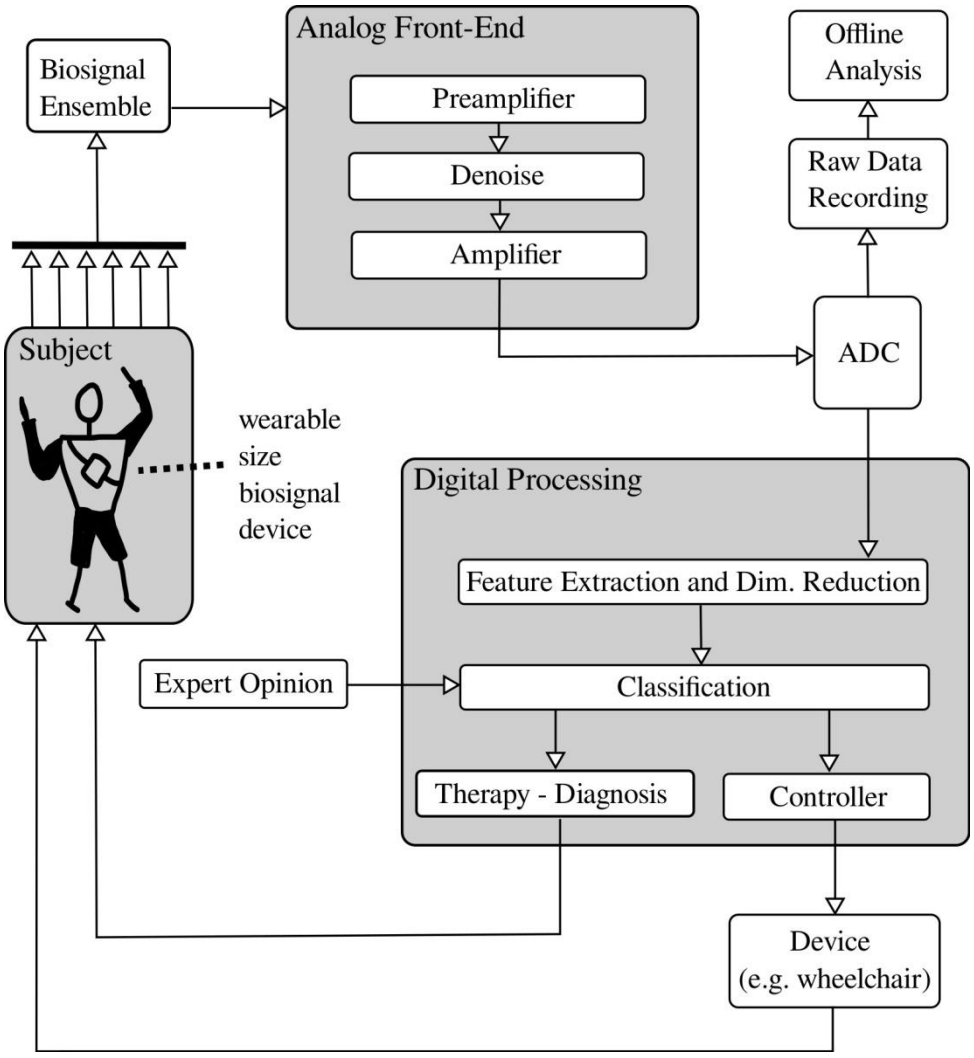

Fig. 2. Platform for joint analysis of biosignals ensembles

Figure 2 presents a detailed panorama of the elements of our platform that we will describe as follows: The subject under study is sensed using a wearable size biosignal device, where the data acquisition part is executed. For example, we can consider an array of sensors for every lung EMG signals, another sensor for ECG and microphone sensors to record the audio of the respiration activity. In the *Analog Front-End* subsystem every analog signal is pre-amplified, de-noised, and post-amplified in order to achieve the voltage level required to convert the analog signal to digital (ADC) without a considerable amplification of noise. The ensemble of digital signals obtained is raw data and can be stored in this step for offline analysis.

The *Digital Processing* subsystem is the most important part of the platform, and its global objective is to convert the biosignals ensemble into high-level information useful for the specific application, for example diagnosis, therapy design, or controlled actions to devices (as in the case of wheelchair control). The first step in the processing is *Feature Extraction and Dimensionality Reduction.*

For feature extraction, the data is filtered in order to obtain only the features under study, specific for the problem. For example if we are interested in the behavior of the muscle activation while lifting loads, then the EMG data can be filtered to include only the events of load-unload and discard the rest time and/or incomplete loads.

For dimensionality reduction the data are filtered at the level of arrays, and given that neighbor sensor data can be highly redundant, a projection of the array is chosen to represent the data. Principal component analysis (PCA), independent component analysis (ICA), locally linear embedding (LLE), singular value decomposition (SVD) and non-negative matrix factorization are techniques used to compress the signals in a suitable compact description of the signals ensemble.

After the *Feature Extraction and Dimensionality Reduction* step, data are organized using very high level constructs; generally in the form of specialized data structures that were predefined when the objective of the signal processing problem was stated. The design of problem-specific data structures needs to be integral with the *Signal Processing* subsystem, in order to reuse the structures in all the different steps of the subsystem.

The *Classification* step is qualitatively different from the previous steps because the available information at this stage can be presented in a format specially prepared for experts (in this case physicians specialists). Experts can select the samples that give important evidence for the study, and can tag regions of interest on the data. The classification part can be done automatically after the system have been trained using the expert information. The classification need to be evaluated and validated. The Classification step can be targeted to Diagnosis or Therapy, were Diagnosis will provide useful information to support a medical decision over the condition of a patient.

Therapy considers a dynamic relation between the information provided for the system and the therapy selected thereafter, the therapy need to be adjusted dynamically to the reaction (of absence of reaction) of the subject under treatment, in an iterative manner.

In the *Controller* step, the biosignal information is used to control and interface mechatronic devices. A non-directly medical objective of the processing of biosignals is the control of devices of any kind. From the point of view of human-computer iterfaces, biosignals can expand the current mouse, keyboard and touch-screen human interaction to muscular activation. For the majority of people with limb disabilities, the triggering of EMG still occur and can be used for controlling computer-based devices. The triggering of EMG signals can also be used to control prosthetic devices.

In figure 3 we present the main hardware and communication elements of our design for the wearable size device.

Sensor arrays are connected to the *Analog Front-End* subsystem, where the analog signals are amplified to the levels required for the ADC part. The *Analog Front-End* can be composed for independent units for every channel sensed. Sensors are cheaper and easy to obtain that a robust *Analog Front-End* system, then is possible to add a multiplexer (mux) to feed multiple channels into a single amplification unit. A demultiplexer (demux) is required in this case, to retrieve the original signals after the ADC part. To synchronize those processes, it is convenient to program the muxing and demuxing logic in a single application, which shares the same clock. This case is ideal for a FPGA implementation. An FPGA processor is a powerful alternative to a Digital Signal Processing (DSP) System on Chip (SoC), with the versatility and the advantages of a reconfigurable computing unit. Fine-grained control over the mux-demux process have many advantages, for example noisy channels or irrelevant sensors can be turned off dynamically, monitored and re-enabled if required.

The FPGA device that we use has two analog input channels, and our *Analog Front-End* system is composed by two single-channel modules. For every channel a complete array of sensors is muxed, to maintain a static configuration of the amplification level for every unit, because the amplification is dependent on the type of biosignal sensed.

After DAC, the digital signal is processed in the FPGA device. For *Digital Processing via FPGA* we are using a Xilinx FPGA, of the Spartan 6 family, with hardware design specified using VHDL. After the processing, the data is transmitted to an ARM-based microcomputer, connected via USB. The *Microcomputer ARM* is used as a server for data monitoring and transmission, and can be consulted via radio communication, using low-power Bluetooth communication device. The *User Interface*, connected via Bluetooh enables user-friendly interaction on standard PCs, tablets, and smartphones, to review or explore the information processed by the system. In the next iteration of our design, a new generation SoC with ARM processor and FPGA will replace the microcomputer and the FPGA, reducing at the minimum the size of the digital part of our platform.

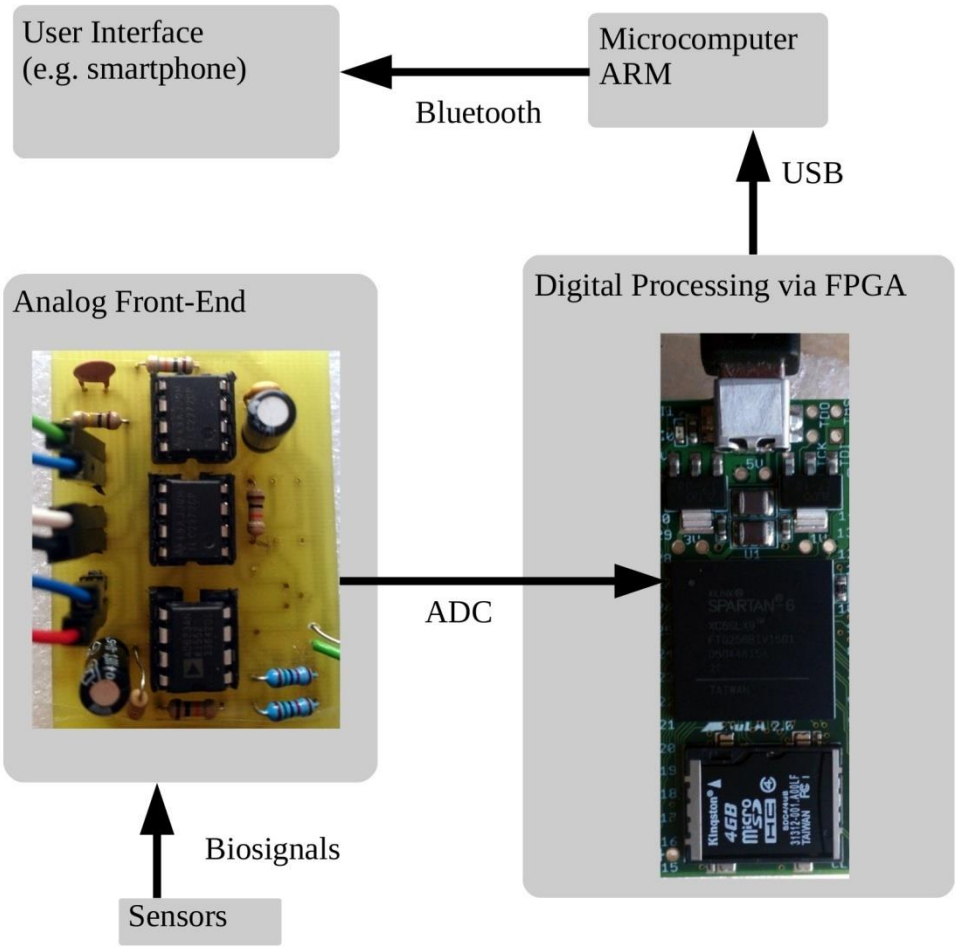

Fig. 3. Platform components

4. Conclusions and further work

The capabilities of current processing units make it possible to produce high-level results, i.e. human understandable from low-level raw biosignals ensembles. With new technology in biosignal sensing, the experience of self-measurement can be more comfortable for the patient. Online indicators of complex measurements, in our case mutual information, can contribute to substantial improvement of the quality of life of people with disabilities or with an unstable health condition, facilitating the medical treatment.

In our platform we use two processing units, a FPGA processor for the digital signal processing part, and ARM processor that acts as a server for the communication between the digital outputs and the final user interfaces. In the next iteration of our design, we will combine the two processors in one SoC with ARM and FPGA cores. This choice has many advantages, for example the complexity of the system will be reduced, and also the overall size and weight of the wearable-size device.

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