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Distributed Measurement Unit for Closed-Loop Functional Electrical Stimulation: Prototype for Muscular Activity Detection

Guillaume Coppey, David Andreu, and David Guiraud,

Abstract— **One way to face centralized Functional Electrical Stimulation (FES) architecture limitations is to distribute electronics close to electrodes. These Distributed Stimulation and Measurement Units (DSU and DMU) are interconnected by a network. This paper focuses on the design and prototyping of a DMU dedicated to ElectroMyoGramm (EMG) activity reading. The paper exposes the embedded digital architecture as well as results of EMG activity detection.**

I. INTRODUCTION

FES may restore motor functions of paralyzed muscles. For complex tasks either for rehabilitation in a clinical context or for movement restoration, multi-site FES is mandatory because several muscles have to be activated, and close-loop control may increase the movement quality. Besides, restoring gait for paraplegic subjects, based on a centralized system [1] leads to many wires, complex surgery and a fixed number of channels. Other works such as [2], use EMG as input signal to drive neural stimulation to control knee angle. Each sensor is connected to a central unit so that the global system is further complicated. Finally, if we consider even more complex stimulation systems such as selective stimulation through multipolar electrodes [3], it becomes almost impossible to connect them to a central unit because of cable count and connectors size.

One way to address these issues is to distribute electronics and software close to the sensors / electrodes. It induces a network architecture and distributed software over independent and small units. Solutions are proposed based on digital circuits together with wireless link ([4] [5] [6]) but they have a limited data rate and energy efficiency. Network real time features for closed loop control are limited by network capacities and embedded computation power. We proposed a very advanced networked system (figure 1) with far enhanced features [7] that already provides distributed stimulation units with local stimulation pattern management, and advanced Medium Access Protocol (MAC) to allow for deterministic and time controlled data exchange.

To provide power and transmit data, most of the previous works chose RF and inductive coupling solutions. In this case all implanted units must be closed to each other so that one external armband coil covers all sensors or stimulators [5]. Moreover, RF link in implanted systems has a quite low data rate. On the contrary, we developed a 2-wire bus [8]. Besides, in many cases we do not need the raw data from a sensor but processed data. An example is the foot drop correction for hemiplegic patients [9]; they acquire acceleration and angular signals from multi-axes sensors but after processing, only the walking phase is used to modulate stimulation and it needs much lower data-rate transmission.

The paper proposes an implementation on a DMU of digital signal processing commonly used in FES field. Because this work is a contribution in our project of distributed stimulation system, we keep the component design flow based on Petri Net modelling and FPGA implantation. An example of data processing is presented and discussed.

II. MATERIALS AND METHOD

A. Distributed FES Architecture

The distributed stimulation architecture is based on a set of DSU and DMU, connected to a main controller by means of a 2-wire bus. This controller is in charge of executing the FES application (rehabilitation function) managing distributed units. In such a distributed architecture the 2-wire bus is like a backbone, with constraints on both medium access determinism [10] and network throughput since this embedded network only offers a limited data rate notably for energy consumption reasons (low clock frequency of implanted units) [11].

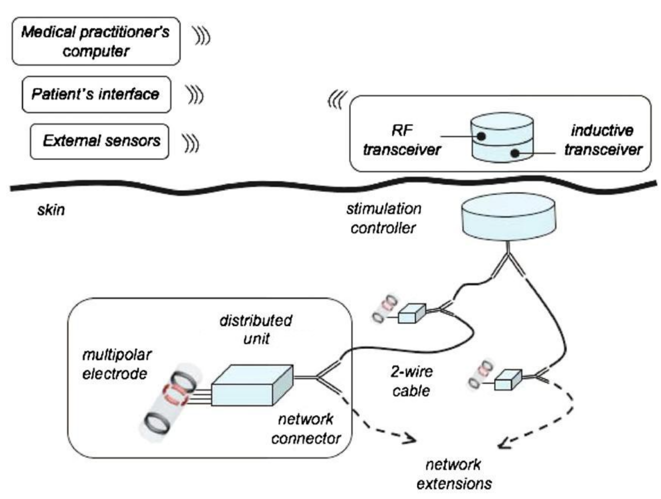

Fig. 1. Distributed architecture for neural electrical stimulation

DSU has already been prototyped, we focus in this paper on DMU design and prototyping.

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B. Distributed Measurement Unit

Dealing with closed-loop FES control and event-triggered FES, both trying to improve stimulation efficiency and to minimize energy consumption, needs for sensors. Depending on the rehabilitation function to be performed, several kinds of signals can be measured; physiological signals like ENG (electroneurogram) and EMG [12], or physical ones like acceleration, inclination or pressure [9]. The DMU embeds a set of functionalities (Figure 2):

- A digital acquisition front end to collect data from the sensor, with an Analog to Digital Converter (ADC).
- Filtering of input data to remove ambient or conversion noises. In our case, an Infinite Impulse Response (IIR) filter is used, also allowing for data scaling.
- Memorizing data samples at different steps, from raw data to processed data. This memory size being limited since embedded in the implantable device.
- Depending on the application, advanced signal processing are implemented. Distributing this treatment on the DMU reduces the controller load as well as the network traffic: computing the envelop of an EMG signal, determining the walking phase for assisted walk in hemiplegic patient [9], detecting a threshold crossing event for sit-to-stand movement initiation [13]. These treatments use the previously mentioned memory to store intermediate and final data.
- Communication facilities offering several modes to transfer data to the controller:
  - Periodic raw or processed data exchange, as for instance for the closed-loop control.
  - Event notification, as for example for a sit-to-stand movement based on a triggered stimulation. Notifying events avoids to monopolize the medium by periodically sending data samples.
  - Data transmission on request, when the controller needs a single data sample (calibration procedure for instance).

  The switch block shown on figure 2 manages memory access, for data to be available from the embedded protocol stack [11].
- DMU managing in terms of blocks configuration and interconnection required by the controller.

C. Implementation on FPGA

For compactness and energy consumption reasons, the technology on which we implement DMU is FPGA (Field Programmable Gate Array). Indeed, the FPGA technology allows simultaneously performing several tasks (real parallelism), like data acquisition, processing, communication, etc. without requiring a multitask operating system on a microcontroller neither a high frequency clock to respect time constraints. However the digital architecture to be implemented into the FPGA can be tricky to design and validate depending on its complexity. To face this issue, our methodology is based on components which behaviors are described by means of temporal interpreted generalized

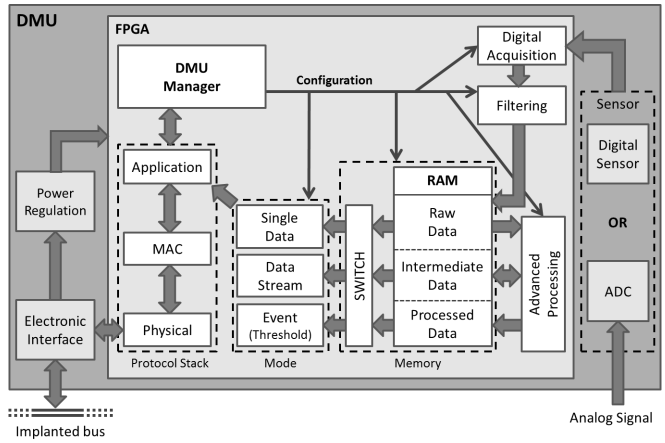

Fig. 2. Distributed Measurement Unit Architecture

Petri Nets (PN) [11]. Each block of the DMU architecture was described by means of the HILECOP software, which supports our PN component based methodology and ensures a direct translation into VHDL code. Following this methodology, components are assembled by means of the ports of their interfaces and doing so the global PN of the system is built [14], global PN on which we then perform a formal analysis of the resulting digital system. Figure 3 shows a part of the PN model of a rolling average component. The first place (a) of this PN part receives a token from the filtering component, indicating the availability of a new sample. Place (b) is shared the DMU manager component, allowing it to select or to by-pass the rolling average process. Treatments to be performed on data are described by means of VHDL functions associated to transitions of the PN model, as shown on figure 3; a function is executed when the corresponding transition is fired. Functions associated to the given model are:

- *mean_abs* calculates the absolute value of the filtered EMG data sample.
- *mean_sums* adds the last sample value to the $n - 1$ previous samples (n being the configurable number of sample of the rolling average).
- *mean_update* updates the mean value with the previously computed sum.
- *mean_test_i*, *mean_inc_i* and *mean_reset_i* manage the circular buffer in which values are stored.

D. Prototype of DMU

To validate both the digital architecture of the DMU and the digital processing it performs, we prototyped a DMU in charge of muscular activity detection. This DMU is able to detect a threshold crossing on an EMG input signal. This can be useful to trigger an electrical stimulation sequence as in [15]. The experimental setup is schematically represented on figure 4, showing also the digital architecture of the prototyped DMU.

EMG is measured on the extensor digitorum communis with surface electrodes to detect a wrist extension. EMG signals are amplified by a BIOPAC EMG 100C module. The

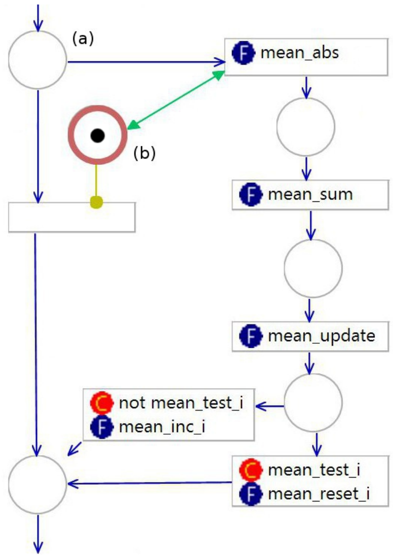

Fig. 3. Petri Net implementation of rolling average. (a) is a standard place, (b) is a shared place, F is a function, and C is a condition.

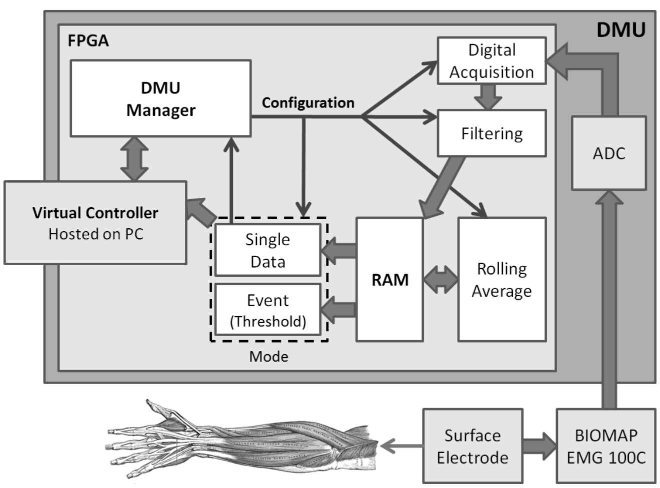

Fig. 4. Experimental setup

resulting analog signal is sampled by a ADC (Microchip MCP3204) at $5kHz$ with $12bits$ resolution. The second order IIR low-pass filter is configured at $F_c = 200Hz$ with a quality factor of $\xi = \sqrt{1/2}$ to extract the useful signal in the most relevant bandwidth (coefficients are computed on Matlab by discretization of second order linear transfer function, and sent to the DMU). To detect muscular activity from EMG signal, its envelope is computed. The solution we adopted is a rolling average on 128 samples of EMG absolute values. Finally a detection component allows detecting if the envelope signal has crossed a given threshold.

All parameters (cut-off frequency, threshold value, samples count for rolling average...) are configurable by controller requests. For this prototype, to simplify data exchange, we designed a virtual controller on a Personal Computer. A friendly interface based on Matlab GUI allows to: adjust the filter, send corresponding parameters to the DMU, and display the EMG envelope processed on DMU.

III. Results and Discussion

The extensor digitorum communis EMG signal (figure 5) has a mean magnitude of $300\mu V$ considering absolute value during an activity phase of $100ms$ (figure 6).

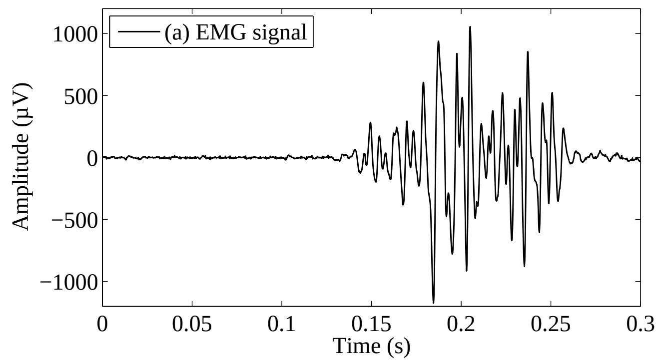

Fig. 5. EMG signal acquired on extensor digitorum communis muscle

DMU is able to accurately detect this activity after filtering and then processing a rolling average. Figure 6 shows intermediate signals: (a) is the absolute value of the filtered EMG signal, (b) is the rolling average, and (c) is the threshold used for activity detection.

We compared the filter and rolling average processed by DMU versus that processed by computer. DMU use $16bits$ integer processing with a low frequency clock of $1MHz$ like in DSU. On computer, algorithm where computed on Matlab software, with a dual-core processor working at $2GHz$. Both system use same algorithm and same raw EMG signal sampled by the DMU ADC. Results obtained using these two processes are identical except a slight difference on the time instant at which the threshold crossing is detected. So we have measured this difference on a test campaign of 50 trials and we have obtained $236\mu s$ (DMU detection being late) with a standard deviation of 0.043%. Comparing this time difference to the activity phase duration of around $100ms$, we can consider that our DMU processing is running properly.

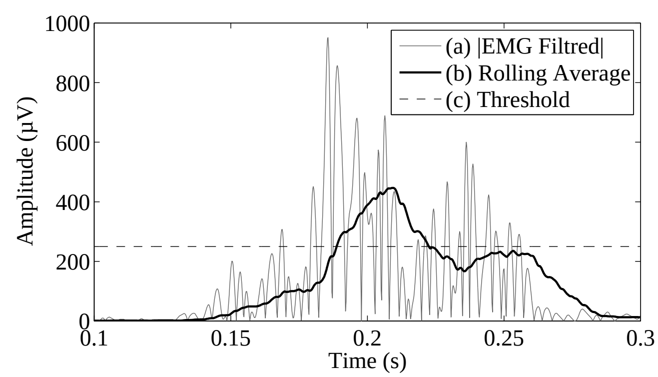

Fig. 6. Intermediate signals for muscular activity detection on extensor digitorum communis: (a) is the absolute value of filtered EMG signal, (b) is the rolling average processed by the DMU, and (c) is the threshold configured in the DMU.

Besides, the use of this average method induces latency because the average signal crosses the threshold after the raw signal. So we computed the detection latency for different rolling average configurations, modifying the number of samples it is based on. Table I shows the mean value of the detection latency, performing 50 trials for each case.

However, this latency has to be compared with the global chain duration:

- complete detection latency (sampling duration, average duration, other protocol staff),
- communication delay,
- controller operation duration,
- stimulation latency,
- muscle activation time response.

Number of samples	16	32	64	128
Latency (ms)	7,64	12,0	15,6	22,7

TABLE I
LATENCY

Increasing the number of samples smooths the envelope of the signal and limits the false detection risk (due to artifact occurrence for example). In the other hand, reducing the number of samples reduces the detection latency as well as hardware resources (so reduced chip area and static power consumption). Modifying the sampling frequency reduces the dynamic power consumption, impacting necessarily the detection latency. So for each application there is a trade-off between false detection robustness and detection delay, dealing with artifact property (amplitude and duration), functional time constraints and hardware resources.

IV. CONCLUSIONS AND FUTURE WORKS

This DMU prototype showed that digital processing chain dedicated to EMG activity detection can be embedded within a distributed measurement unit using a programmable logical device (FPGA), like we did for distributed stimulation unit. The embedded architecture of this unit is designed according to a Petri Net based methodology. This allows to exploit effective parallelism offered by FPGA devices, and to reach expected performances even at low frequency. The embedded processing chain is configurable and parameters can be adjusted, in order to optimize performance.

Future works will consist in adding the protocol stack to the digital architecture of the DMU, allowing integrating it within our distributed FES architecture. This will allow us to measure effective latencies and other performances from a closed-loop point of view. This work is necessary to ensure that such a distributed EMG activity detection is adequate with FES requirements. After that, we will investigate the trade-off between the global performances versus the implantable device constraints, like its size and power consumption.

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