Design Challenges for Wearable EMG Applications

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***Abstract*—Wearable technologies are changing the way we deal with health and fitness in our daily life. Nevertheless, while MEMS-enabled inertial sensors have conquered the consumer market, physiological monitoring has still to face barriers due to the complexity and costs of physical interfaces (e.g. electrodes), the degree of intuitiveness of the interaction and the processing required to reach satisfying performance. These limitations are mitigated by the embedded systems' growing integration of interfacing capabilities and efficient computing power. In this paper, we describe the main applications and the related technologies for the acquisition and processing of myoelectric (EMG) signals. Starting from well established active sensors and bench-top setups, we introduce a recent design based on the combination of an integrated Analog Front End (AFE) and embedded processing. This solution provides high quality signal acquisition and on-board digital processing capabilities with a contained power consumption. The system was tested within the prosthesis control application scenario, one of the most stringent EMG applications, achieving a 90% gesture recognition accuracy with real time on-board processing at a power consumption of $30\,mW$. Such promising results highlight the current trend in shifting EMG applications from dedicated analog solutions towards integrated digital devices, favouring the development of advanced, modular and low-power wearable solutions.**

I. Introduction

Recent advancement in technology has led to the availability of powerful solutions for sensing and processing in shrinking footprints, at a relatively low cost and low power consumption. In a few years, for example, the integration scale of MEMS devices moved from single axis sensors (e.g. accelerometers) to sensor hubs with multiple sensors and processing capabilities (e.g. an Inertial Measurement Unit with a dedicated processing core). Furthermore, we can now buy for few dollars low-power 32-bit microcontrollers (MCUs) with rich interfaces and functionalities, delivering unprecedented processing power. This enables the possibility to bring intelligence close to the source of information, executing complex algorithms near the sensors and thus optimizing the trade-off between energy efficiency and performance [1], [2].

Sensing and computing developments, together with low power communication solutions, enabled the diffusion and adoption of a wide range of wearable devices, influencing application domains such as wellness and healthcare. While inertial sensors, for example, have reached a high level of maturity and are now embedded in a wide range of devices with ubiquitous use (e.g smartphones or activity trackers), physiological sensing is still facing challenges towards universal adoption. Among others biopotential signals, superficial electromyography (sEMG or EMG) has been successfully used in medical and research applications for decades, studying a wide range of motor and neural conditions [3]. However, it is now experiencing a growing interest thanks to the recent availability of novel low-end commercial products [4]. EMG applications span from clinical diagnostics, to prosthetic control and up to interactive applications and Human-Machine Interfaces (HMIs). Despite the research community is very active in this field, still many challenges remain unsolved and the road to versatile wearable EMG devices is still long.

To cover the gap from research to commercial products, we must consider that sEMG can be used in several scenarios. For the sake of simplicity, we identify four application categories. A first one is the use of EMG signals in clinical diagnostics [5]. The corresponding high-end and high cost equipment (up to hundreds of K€) privileges the quality of the collected signals, using expensive electrodes and complex conditioning and acquisition devices, which provide multiple acquisition channels at high sampling frequencies. Furthermore, it can rely on a controlled lab setting and it mainly targets offline data analysis. Electrodes placement is controlled by the clinician, the patient is steady and the limited duration of the acquisition guarantees lower noise with respect to daily life and wearable scenarios.

A second scenario is the use of EMG for prosthesis control [6]. This is a challenging situation under several constraints, falling within the HMI domain: the muscle activation corresponding to the intended motion is sensed through EMG signals and translated in a command/actuation pattern for the prosthesis. In this scenario, several conditions must be accomplished: from the intuitiveness of the control strategy to the strict real-time requirements (movement recognition time below 200ms [7]); from the need to handle consequences of a non-ideal setting (daily life conditions imply changes in sensor placements, interference from other non-targeted body movements, variable repetitions of the target movement, etc.) to the acceptability and wearability of the device. Since active prostheses are a replacement of a lost functionality, costs are tolerated in a range of thousands of Euros, but only if justified by high performance and enhanced functionalities.

Motor rehabilitation is a third scenario where EMG can be beneficial, in applications such as EMG-driven exoskeletons [8] or serious games for physical training [9]. Serious games are nowadays exploiting wearable inertial sensing, pressure mats or vision-based input devices to monitor and provide feedback to patients during physical exercises. The performance-cost compromise is here lowered from the previous cases and it targets systems for easy deployment and at-home use, with particular care to usability. In this case,

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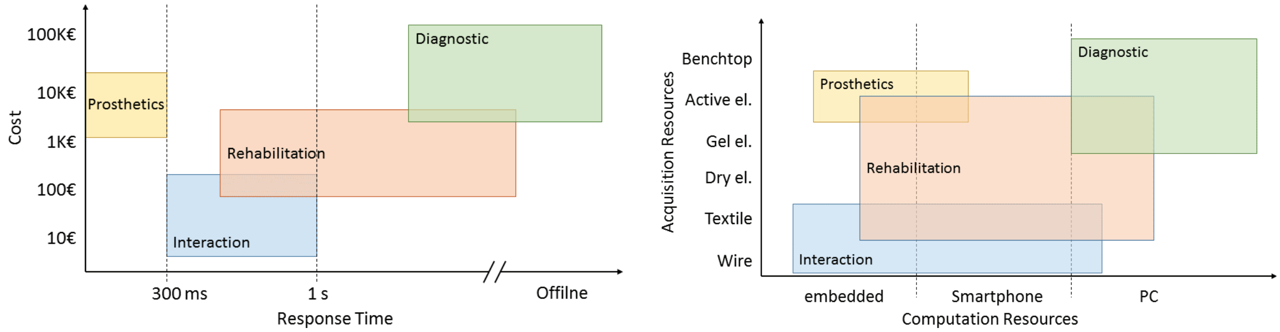

Fig. 1. Resource needs and constraints for the main EMG application scenarios.

EMG sensing is a component of a more complex system an its impact on the overall costs must be limited, but the integration with other sensing modalities and the use of sensor fusion techniques mitigate also the performance requirements.

A fourth scenario is the use of EMG signals for interaction and general HMI applications [10]. In this case, the requirements on the quality of the signal can be lower than in medical grade devices and the set of movements/gestures recognized can be reduced w.r.t. prosthetic applications. Real-time motion recognition and user comfort are still important requirements, but the overall accuracy and the complexity of the algorithms can be lower than in the previous scenarios. Those interfaces are for consumer market and therefore a low-cost within few hundreds euros is expected.

The use scenarios are illustrated in Fig. 1, which summarizes the main requirements for such EMG applications in terms of cost, response time, acquisition and processing resources. In this work, we first review the acquisition and processing modalities to cover the whole spectrum of EMG applications. We then focus on the prosthetics control use case and we present the outcomes and the lessons learned in the development of an embedded platform for EMG acquisition and processing, thought for intuitive control of an upper limb prosthesis. We will focus on two main aspects: the interface for the acquisition of the EMG signal and the signal processing approaches for the implementation of natural interaction strategies.

The reminder of the paper is organized as follows. Section II describes technologies used for EMG acquisition and processing and will give an overview of the main application domains. Section III presents a comparison between EMG gesture recognition performed with high-end offline platform and an integrated wearable solution. Finally, Section IV draws the conclusions.

II. Background and Technology

A. EMG Signals and Acquisition Systems

The EMG signal is the superposition of the Action Potentials (APs) of the muscle tissue cells occurring during a contraction. APs are the result of neural spikes sent out from the nervous system to the muscles to perform the contraction, which propagate trough cellular membranes and result in a variation of electrical potential. The resulting electrical activity is the EMG signal and it can be acquired by surface contact electrodes and appropriate conditioning circuitry. Its amplitude is contained in the $\pm 10\,mV$ range with a maximum bandwidth of $2\,kHz$. These parameters depend on the diameter of the contracting muscle and the distance between the active muscle fiber and the sensing site. Surface EMG signals are affected by several sources of interference, such as the power line noise or the high signal variability caused by the contact impedance of the sensors, the skin perspiration and by the crosstalk between adjacent muscular fibers.

The EMG acquisition is performed through surface sensors that are composed by two conductive plates each one connected to the inputs of a differential amplifier, thus sensing the aggregated APs of the underlying muscles. In clinical practice, EMG acquisition is performed by dedicated bench-top medical instrumentation [11]. Typically, they employ silver-chloride (Ag/AgCl) electrodes with the addition of a conductive gel to minimize the contact impedance with the skin. These systems provide very high quality signals, with sampling frequencies of up to $10\,kHz$. Moreover, the conditioning electronics is capable to analyze the EMG signal at the AP level, allowing accurate diagnostic investigation of neural and muscular systems. Dedicated acquisition systems are also used in research applications, since they provide high quality signal for the study of gesture recognition and HMI applications [12], [13]. Some of these systems allows to acquire up to 400 EMG channels and thus they consent the analysis of algorithms based on dense matrices of EMG sensors. Nevertheless, this approach is confined only to research evaluations, since its complexity and cost is not suitable for an out-of-the-lab deployment.

Wearable EMG applications require acquisition interfaces that meet strict constraints in terms of form-factor and power consumption. In prosthetic applications, the preferred solution is represented by active sensors, such as the Ottobock 13E200 [14]. These sensors are designed with 2 metal electrodes for the differential acquisition of the signal and one additional reference electrode. They are equipped with a miniaturized circuit board populated with the analog circuitry necessary for signal conditioning and amplification. The raw differential EMG signal is low-pass filtered, then amplified by a differential stage and finally integrated to obtain a single-ended enveloped EMG trace. The output of active sensors depends

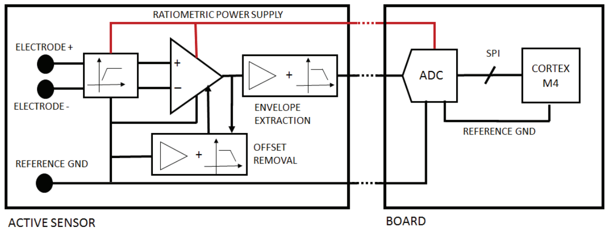

Fig. 2. Active sensor architecture diagram. The EMG signal is pre-processed by the sensor's internal circuitry. Power supply and ground reference are provided by the acquisition board.

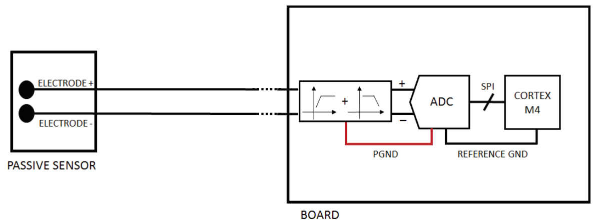

Fig. 3. Passive sensor architecture diagram. The EMG raw signal is acquired by the on-board ADC and pre-processed digitally by the microcontroller.

on the used power supply and usually spans between 0 and $3.3\,V$, making it suitable for the acquisition by an embedded ADC integrated in modern MCUs. An architectural diagram of active EMG sensors is reported in Fig. 2.

The signal provided by active sensors is ideal for prosthetic applications where it is important to extract the information related to the muscular contraction level. This information is used by the prosthetic controller to detect the desired movement and actuate the prosthesis. However, the analog conditioning of these sensors reduces the signal's bandwidth, limiting the possibility to extract features in the frequency domain. Finally, the high cost of these devices limits their use to medical and prosthetic applications.

Recent trends in the design of low power integrated signal converters [15] and the growing interest for biopotential processing applications [16] are providing an alternative approach for the acquisition of EMG signals with passive sensors. Such approaches are ideal for wearable applications, moving signal conditioning and processing from dedicated analog circuitry to integrated low-power digital devices. A solution for the acquisition and processing of biopotentials is described in [17], [18], where the authors showed a system architecture based on Cerebro, a custom integrated Analog Front End (AFE), and an ARM Cortex M4 MCU. Here, the EMG signal is acquired through passive low cost electrodes and thanks to on-board digital processing the system delivers the same signal quality as with active sensors. The architectural scheme of a passive EMG system is represented in Fig. 3. This approach allows a wider signal bandwidth and the application of advanced feature extraction techniques, such as frequency and wavelet domain features [19], fostering the research in digital architectures that address the processing of considerable amounts of data in real time with a limited power budget [20].

B. Signal Processing Platforms and Algorithms

In commercial prosthetic systems, EMG-based control strategies rely on predefined sequences of muscular contractions, which are associated to commands for the prosthesis. This method is adopted for its robustness, but it is not intuitive, requires a high level of concentration and a long learning curve. Current research trends aim at the design of systems based on natural control strategies, where the prosthesis is actuated through intuitive commands.

The pattern recognition approach, widely investigated at research level, is based on machine learning algorithms that recognize and classify the level of activation of the forearm muscles to decode the intended gesture. The algorithms most extensively used in these applications are supervised classifiers, such as LDA [21], ANN [12], or SVM [22]. Some attempts have been made also with unsupervised techniques like clustering or with deep learning techniques, such as the Convolutional Neural Networks (CNN) [23]. The basic idea of this approach is to train a classifier with sample gestures performed by the user and use it for online classification of the muscular activation patterns of the hand gesture.

Most of the literature contributions are focused on the development and evaluation of recognition algorithms. Datasets are collected for offline analysis on high-end PCs [24]. On the other hand, recent studies started the analysis of the processing platforms needed for online recognition and introduced the use of wearable systems. In particular, the works of Zhang [25], [26] present an open source platform based on a ARM Cortex-A8 processor that matches the requirements to execute real time gesture classification. However, the power consumption of this platform is in the order of watts, thus limiting its use for low power applications. The embedded platform presented in [18], based on a Cortex M4 MCU, is capable to read up to 8 EMG sensors and execute the SVM classification algorithm in real time ($< 10ms$), with a power budget of few milliwatts. It is therefore a qualified first step towards the wearable domain, aiming to run gesture recognition algorithms on ultra low power platforms. The trend to design novel low cost wearable and consumer man-machine interfaces contributes to push the miniaturization and development of less intrusive and more efficient EMG systems [4].

III. Experimental Results

In the previous Section, we introduced several systems for the acquisition of EMG signals and we highlighted the solutions suitable for wearable use. Next, we are going to evaluate state-of-the-art systems by directly comparing the EMG signals they provide and by evaluating how such signals can be used for hand gesture recognition. In particular, we consider 3 acquisition setups and the related datasets, ranging from a PC-based bench-top solution to an innovative wearable device we developed.

Ninapro Dataset. The Ninapro database contains the most complete dataset for EMG-based gesture recognition published up to date [27]. It collects 52 hand gestures performed by 27

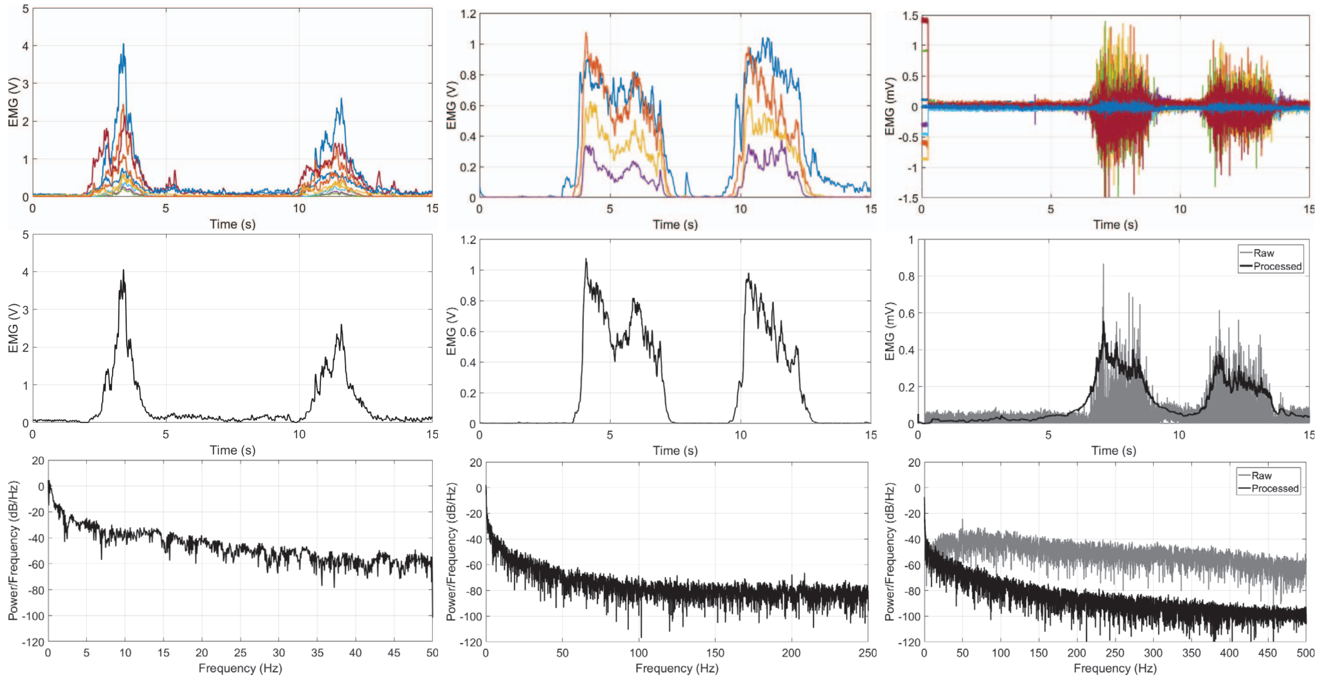

Fig. 4. Samples of EMG signals acquired while executing a power grip: (left) Ninapro database acquired using Ottobock active sensors with dedicated acquisition board for PC; (center) UNIBO dataset acquired using Ottobock active sensors with embedded ADC; (right) Cerebro dataset acquired using passive electrodes and Cerebro AFE with embedded MCU. Top line: acquired signals; center line: detail of one signal; bottom line: FFT of the selected signal. For the Cerebro dataset we report the raw acquired EMG signal (grey) and the result of the digital pre-prcessing (black).

users, while wearing a complex set of sensing devices. In particular, 12 active EMG sensors (Ottobock 13E200 [14]) were placed on the user's forearm and their output was acquired by a PC through a dedicated acquisition card (National Instruments NI-DAQ PCMCIA 6024E, 12-bit resolution, $100\,Hz$ sampling). Moreover, inertial sensors and a 20-segment data glove complete the acquisition setup. Here, we consider only the EMG signals and we will use this dataset as the reference. An example of the acquired signals is shown in the left column of Fig. 4. Detailed information on the dataset and its characterization can be found in [27].

UNIBO Dataset. The UNIBO dataset was acquired at the University of Bologna and it contains 5 gestures performed by 9 users [28]. This dataset collects a smaller number of gestures, but they represent the core interaction needs for prosthetic use (open hand, power grip, 2 fingers pinch, 3 fingers pinch, pointing index and rest). Moreover, the users performed the same set of gestures while keeping the arm at 4 positions and during 10 sessions, to test variability and robustness of the classification algorithms. In this case, 4 active EMG sensors (Ottobock 13E200 [14]) were fed in a custom embedded board and acquired at $500\,Hz$ by the internal ADC of the MCU. During collection, the data was via Bluetooth to a PC for offline analysis. Sample signals are reported in the central column of Fig. 4 and further details can be found in [28].

Cerebro Dataset. The Cerebro dataset was acquired using a custom embedded board [17]. This is a fully embedded and wearable solution where the EMG signals are sensed by passive low cost electrodes and they are fed directly to the board for acquisition and on-board processing. Signal DC offset is removed by a digitally controlled feedback loop [29] and further filtering is performed on the MCU to obtain a single ended EMG signal used for classification [30]. The embedded platform is also capable of running a SVM-based recognition algorithm for on-board real-time recognition of the performed gesture. For the acquisition of the dataset the pre-processed signals were streamed to a PC via Bluetooth. This dataset considers the same set of 5 commonly used gestures as the UNIBO dataset, which were acquired using 8 EMG channels and evenly placing the electrodes around the user's forearm. Example signals are shown in the right column of Fig. 4 and further details can be found in [18].

A. Signal acquisition and conditioning

In Fig. 4 we show the signals from the three considered datasets in order to compare their acquisition setups. Here, we show an example of the acquired signals relative to the execution of two repetitions of a power grip gesture (top row), the detail of one of the signals (middle row) and its frequency spectrum (bottom row). The Ninapro (left column) and UNIBO (middle column) datasets have been acquired with the active Ottobock sensors, which provide a single ended amplified and filtered signal, ready for the use in gesture recognition applications. The Cerebro AFE, on the other hand, provides a differential EMG signal with a hardware offset compensation, which is then digitally processed to extract a filtered single-ended signal. The raw and processed signals are

TABLE I
AVERAGE RECOGNITION ACCURACY FOR DIFFERENT DATASETS.

Dataset	**Accuracy (%)**
NINAPRO All	76.3
NINAPRO Reduced	89.8
UNIBO	88.9
Cerebro	89.2

shown in the middle row of the right column in Fig. 4 and their frequency spectrum is shown in the bottom row.

The sampling rate differs among the three datasets since the use of active sensors allows to lower the acquisition frequency without considerable loss in signal quality. However, the Cerebro platform offers a higher sampling frequency and with the on-board processing capabilities it allows to obtain comparable signal quality to the Ottobock sensors, providing advantages in reduced size, cost and power consumption. While the active Ottobock sensors remain the state-of-the-art for clinical signal acquisition, the integrated Cerebro approach offers a valid alternative optimized for wearable devices.

B. Gesture recognition

The main purpose of the collected datasets was to evaluate the use of EMG signals for the recognition of hand gestures, and the development of natural interaction modalities for hand prosthesis. In particular, the Ninapro dataset establishes a benchmark in this field, considering the variety of gestures represented and the high number of users executing them. Its 52 total gestures include individual finger and wrist movements, hand postures and several grasping and functional movements. With such data, several classification approaches have been compared, including time and frequency domain feature extraction techniques (mean, variance, waveform length, FFT, DWT) and classification algorithms (LDA, kNN, ANN, SVM). Results show that the best combination is to use the signal mean as input feature and the SVM with a Gaussian kernel for recognition, achieving a mean classification rate of 76.3% across all users.

The other two datasets presented in this work focus on a more limited number of gestures, which identify the core interaction needs for the control of a hand prosthesis. When considering such reduced gesture set, the accuracy of the recognition on Ninapro data increases up to 89.8% (Ninapro Reduced). Applying the same classification approach to data from the other two datasets, we achieve the same recognition accuracy, as illustrated in Table I. Accuracy values highlight the equivalence of the compared acquisition setups when gesture recognition is the application target.

Beside the offline analysis of the gesture recognition accuracy, the Cerebro platform allows also a full implementation of the classification and control strategies. With this platform, a complete system for acquisition and processing of EMG signals can be deployed [18]. In particular, the embedded MCU is equipped with a hardware Floating Point Unit and a dedicated set of DSP instructions, allowing for an efficient trade-off between processing capabilities and power consumption (210 DMIPS at 280 $\mu A/MHz$ current consumption, with a maximum 168 MHz frequency). The processing and memory requirements for the SVM recognition algorithm are defined by the number of Support Vectors in the trained model, which in the performed tests was always below 500. On the Cerebro platform, this translates in computational times below 1 ms for the run-time classification of a new sample and an overall memory occupation of 15 kB. This results in a 30 mA power consumption for real-time EMG acquisition, pre-processing and on-board classification of the performed gesture.

IV. CONCLUSION

Surface EMG signals are an interesting source of data, complementary to the existing ones in several application domains, from clinical practice to human machine interfaces and thus it is a candidate for future wearable solutions aimed at improving the quality of our daily life. When compared with inertial sensing, EMG solutions require more discreet motions to classify movements (i.e. muscle contractions), while they share the advantages of not suffering from occlusions and bounding to area under monitoring typical of vision-based techniques. In this paper, we evidenced the challenges and trends towards a wider and more effective use of EMG sensing, considering the lesson we learned in the prosthesis control scenario. Challenges are related to design issues such as electrodes and the complexity and constraints of the processing, particularly in applications where both accuracy of the recognition and real time performance have strict requirements. However, technology is coming in help. In fact, the computational power to implement near-sensor processing matching the required performance is available now in commercial low-power MCUs and will augment in future years. Therefore, we can substitute active electrodes with passive ones coupled with dedicated AFEs and combined with digital signal processing. This approach benefits from the increasing technology integration and improves the performance vs cost trade-off. Furthermore, the shift of the intelligence from the analog section of the active sensors towards digital processing enables the development of modular and ultra low power devices.

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