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A Versatile Embedded Platform for EMG Acquisition and Gesture Recognition

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***Abstract*—Wearable devices offer interesting features, such as low cost and user friendliness, but their use for medical applications is an open research topic, given the limited hardware resources they provide. In this paper, we present an embedded solution for real-time EMG-based hand gesture recognition. The work focuses on the multi-level design of the system, integrating the hardware and software components to develop a wearable device capable of acquiring and processing EMG signals for real-time gesture recognition. The system combines the accuracy of a custom analog front end with the flexibility of a low power and high performance microcontroller for on-board processing. Our system achieves the same accuracy of high-end and more expensive active EMG sensors used in applications with strict requirements on signal quality. At the same time, due to its flexible configuration, it can be compared to the few wearable platforms designed for EMG gesture recognition available on market. We demonstrate that we reach similar or better performance while embedding the gesture recognition on board, with the benefit of cost reduction. To validate this approach, we collected a dataset of 7 gestures from 4 users, which were used to evaluate the impact of the number of EMG channels, the number of recognized gestures and the data rate on the recognition accuracy and on the computational demand of the classifier. As a result, we implemented a SVM recognition algorithm capable of real-time performance on the proposed wearable platform, achieving a classification rate of 90%, which is aligned with the state-of-the-art off-line results and a 29.7 mW power consumption, guaranteeing 44 hours of continuous operation with a 400 mAh battery.**

***Index Terms*—Electromyography (EMG), gesture recognition, wearable device.**

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I. Introduction

THE recent boom of wearable sensors and the large request for user-friendly and natural interfaces have opened the way to the use of physiological signals, typically collected by professionals with high-end instruments, i.e., in medical scenarios, in contexts such as those of our daily life [1]. A plethora of low-cost, wearable devices has conquered the consumer market enabling to monitor user vital signs, activity and behaviors and therefore to influence our daily routines [2], [3]. In particular, electromyography (EMG) enables the detection of the muscular activity and plays an interesting role in gesture recognition and natural interfaces. It is a preferred choice in gesture-based upper-limb prosthetics control, but recently it is gaining the interest of the consumer market [4].

The EMG signal is the superposition of the action potentials of the muscle tissue cells occurring during a voluntary contraction. The resulting electrical activity can be acquired by surface contact electrodes and appropriate conditioning circuitry. Unfortunately, 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 different muscular fibers [5]. Furthermore, the repeatability of the measured EMG signals can be compromised by small differences in electrodes positioning during multiple-session acquisitions and their placement can not be standardized because of the differences in the muscular structure of each user [6].

Even in this highly variable scenario, natural interfaces recognizing the performed gesture can be designed adopting advanced machine learning algorithms for pattern recognition [7]. There have been studies that analyze the recognition strategies, the positioning, the number and the type of EMG sensors in operation to maximize the accuracy of the recognized gestures [8]. In such experiments, active sensors and bench-top acquisition systems are used for signal acquisition and the data processing is performed off-line on a PC. They present promising recognition results, showing the possibility to classify different hand gestures with an accuracy over 90%. Nevertheless, these experimental approaches do not allow to cope with the costraints of size, computational capabilities and power consumption needed for a wearable Human Machine Interface (HMI).

In the commercial state-of-art systems used in prosthetics [9], where the requirements of reliability and robustness are strict, the muscular activity recognition is based on simple threshold detection. The gestures are encoded in predefined bursts of flexions and extensions of the residual wrist muscles. This method does not provide a natural interface while requiring high level of concentration during the use of the prosthesis and a long learning curve [1]. Furthermore, the acquisition of the EMG signals is based on active analog sensors [10]. These sensors perform a fully-analog signal conditioning with discrete components. They include a band-pass filter, a differential instrumentation amplifier and a feedback circuitry for the DC offset cancellation. The pre-amplified signal comes out with a good signal-to-noise ratio and noise cancellation characteristics, but they are expensive and each sensor is enclosed in a separate housing with a big form factor. Thus, they do not allow the design of a low cost scalable and miniaturized system, because the addition of input channels multiplies the needed analog circuitry and impacts on the final cost and dimension of the system.

Although a number of solutions has been proposed, also at chip level [11]–[18], to promote scalability and integration in a EMG gesture recognition systems, currently there are no works presenting a complete system-level approach for signal acquisition and processing. In particular, the signal processing capabilities of all systems found in literature are limited and target low-power sensor nodes, where most of the necessary digital signal processing is performed on an external device in software, e.g., PC or smart phone.

The lesson learned from the analysis of the state of the art in EMG signal acquisition and processing is that the development of a high-performance wearable platform for hand gesture recognition needs a multilevel design approach. In this paper, we present the results of the design, implementation and validation of a wearable EMG acquisition and gesture recognition device. The architecture, first introduced in [19], is based on the Cerebro AFE [20] interfaced with an ARM Cortex M4 microcontroller and merges the optimized design of an analog ASIC with the easy-to-use, low-power and high-performance commercial microcontroller. The achitecture of the AFE allows the system to be used for the acquisition of a wide range of biomedical signals, while the versatility of the microcontroller allows advanced on-board signal processing optimized for the application in use with a low-cost low-power platform. This synergy allows the design of an highly-configurable and scalable system able to provide a high EMG signal acquisition quality, comparable to the state-of-the-art active sensors and an on-board real time signal processing for pattern recognition.

In the previous work [19], we compared our solution with high-end, state-of-the-art active sensors, while in this work we focus on the analysis of the embedded platform, in terms of sensors number and placement strategies and in terms of the trade-off between computation time and classification accuracy. Furthermore, we compare our device and recognition outcomes with the performance of a recently introduced commercial low-cost wearable system, the MYO armband [21]. With respect to it, we perform the recognition directly on board targeting at the same time recognition accuracy and real-time performance.

The introduced approach allows the classification of 7 gestures with a classification accuracy of up to 92%, with a power consumption of 29.7 mW. The results presented here demonstrate the robustness of our approach, reaching the performance of state-of-the-art systems on a miniaturized wearable low-power and low-cost flexible platform.

II. Background and Related Work

Gesture recognition based on EMG signals has been studied in the scientific literature under different aspects for applications in prosthetics and HMI. In fact, a natural gesture interface based on hand movements can enhance the quality of life for upper arm amputees, providing intuitively-controlled real-time systems [22].

Initially, research was focused on the comparison between the various machine learning techniques applied to EMG signals [23]. In particular, approaches based on LDA [24], ANN [25] and SVM [26] classifiers were investigated as the most promising solutions. These studies explore classification of hand gestures on a number of subjects varying from 3 to 6, with a number of gestures ranging from 4 to 9. These approaches compare different classification algorithms, reaching high levels of accuracy (around and beyond 90%), and exploring the use of feature extraction techniques to improve the performance. The high accuracy obtained with all the selected classifiers suggests that the different algorithms are mostly equivalent for the recognition of hand gestures and it is not possible to find a classifier or a feature set that definitively outperforms the others.

The setup and the number of electrodes used for the EMG signal acquisition are further key points with high impact on the design of an EMG hand gesture recognition system. The work in [27] compares the accuracy of systems based on implanted intramuscular and surface EMG electrodes. Results confirm that there is no significant difference between the two approaches in the classification of hand gestures. Passive surface electrodes are compared with active EMG sensors in [28] and [29]. These work analyze some simple hand movements (wrist flexions and extensions and hand pronations and supinations), classifying the EMG signals from 2 couples of active and passive electrodes placed in the same way. In this experiment, the data is collected from 5 subjects and classified using the Auto-Regressive (AR) model. The results show no significant classification difference between the two classes of sensors (85% versus 87% of accuracy). The impact of the number of used electrodes was explored with different outcomes. In [27], results show that on 6 subjects there is no significant improvement with more than 4 sensors, while in [30] the best accuracy tested on 12 subjects is reached with a 7 electrodes configuration and this confirms that to obtain good performance a multichannel approach is desired.

All the described systems rely on high-end data acquisition platforms and perform off-line processing. They do not focus on optimization for resource constrained platforms such as wearables. It has been proven that pattern recognition algorithms can obtain high gesture classification accuracy, but the design of real time efficient systems is still a challenge.

Currently, the most interesting solution for wearable EMG gesture recognition is the MYO armband, from Thalmic Labs [21]. This is a wearable and low cost device equipped with EMG and inertial sensors. It connects to a PC or tablet via Bluetooth Low Energy (BLE) and allows both raw data streaming and the use of a proprietary library for gesture recognition. The signal processing is performed on the host platform and the used algorithms are not documented, but they can recognize 5

TABLE I
COMPARISON WITH STATE-OF-THE-ART AFE ASICS

	ADS1298 TI [31]	ADAS1000 AD [32]	Yazicioglu [11]	Gosselin [12]	Bohorquez [13]	Muller [14]	Lopes [15]	Xu [16]	Teng [17]	Helleputte [18]	**Proposed ASIC [20]**
Applications:	ECG, EEG	ECG	ECG, EEG	EEG	ECG, EEG	EEG	EEG	EEG	EMG, ECG	ECG	**EMG, ECG, EEG**
Technology [μm]:	-	-	0.5	0.18	0.18	0.065	0.35	0.18	0.35	0.18	**0.13**
Supply [V]:	3.0	3.3	3.0	1.8	1.5	0.5	3.3	1.8	1.5	1.2	**3.3**
Power [mW]:	9.5	21	0.2	2.21	-	0.005	5.9[a]	0.7	0.324[a]	0.345	**15**
Electrode channels:	8	5	8	16	1	2	16	8	3	3	**8**
Int. offset compensation:	no	no	yes	yes	no	yes	no	yes	yes	yes	**yes**
Tolerated offset [mV]:	± 425	± 300[b]	± 45	± 450	-	± 50	-	± 250	± 350	± 400	**$\pm$ 300**
IR-noise (1-100 Hz) [μV_{rms}]:	0.53	0.94	0.59	5.4	3.4	3.6	2.9	1.75	21	0.62[c]	**0.82**
Dynamic range [dB]:	115	107	-	-	-	-	60	84	97	110	**108**

[a] power consumption of ADC not included
[b] highest gain setting
[c] for a signal bandwidth of 1-150 Hz

simple hand gestures using the 8 EMG channels and a 3-axes accelerometer. This system represents an innovative platform and the first commercial system for EMG hand gesture recognition. Nevertheless, the device presents low flexibility in terms of possible applications because it lacks embedded computing capabilities and cannot be used as a stand-alone system.

Some attempts in the direction of an embedded platform for hand gesture recognition with on-board computing capabilities are performed in recent work [33], [34]. These works present an architecture based on an ARM Corex-A8 DSP processor and offer an open source platform on which it is possible to run pattern recognition algorithms. The achieved computation time (0.58 ms) matches the real time requirements, but the test dataset includes only one subject with just the recognition of the wrist flexions and extensions and the work does not cope with power consumption or with the issues of EMG acquisition and preprocessing. Furthermore, the used platform is *de-facto* a miniaturized PC and has a power consumption of 1 W limiting its use for low power wearable devices.

For the development of a wearable and low-power system, targeting high accuracy, the most promising approach seems to be the synergy between a low power AFE and a microcontroller, merging the system flexibility with a good signal quality and maintaining a good trade-off between power consumption and computing capabilities.

Some commercial AFE solutions are available on the market [31], [32]. However, the scientific community is also interested in building highly efficient AFEs. In [11], an 8-channel AFE ASIC for EEG acquisition is reported. The ASIC operates efficiently but the platform does not provide signal processing capabilities. A 16-channel ASIC for neural data acquisition is reported in [12]. It has a low power consumption of 2.21 mW, but the proposed AFE introduces a considerable IR-noise (5.4 μV_{rms}) and the ADC only achieves 7 ENOB, hence the system has limited performance. The solution published by [13] is further simplified where only the AFE is designed at chip level. The ADC responsible for biomedical data acquisition is placed off-chip and controlled by an external dedicated DSP. An implantable AFE solution is presented by [14] and a multi-channel programmable IC is introduced in [15], but the authors only present and evaluate the AFE design, with no integration of ADC. An active-electrode solution supporting the use of dry electrodes is presented by [16] and a biopotential front end is presented in [17], again without the integration of an ADC and with only the evaluation of the AFE.

The only efficient solution integrating the AFE with ADC and a microprocessor on the same chip is published by [18] to build a multi-sensor biomedical ASIC. For this purpose, an ARM Cortex M0 processor is used with dedicated hardware accelerators optimized for energy efficient execution of biomedical signal processing algorithms. However, the limited number of sensors (3) affects the system flexibility and limits the possibilities to use this solution in other applications beyond ECG. Table I summarizes the comparison of the aforementioned systems with the proposed solution.

Our goal is to develop a wearable solution, which preserves the data acquisition quality of active sensors, while providing a configurable and scalable solution with processing capabilities. With this approach, we can dramatically reduce the cost of system scaling, for instance bringing from 600$ to tens $ the insertion of a new channel in the system, thus providing a versatile and scalable platform with the additional benefits of on-board processing capabilities. The test results demonstrate a similar performance for our fully embedded and wearable system with on-board computing and the commercial armband with the classification performed on a PC.

III. SYSTEM DESCRIPTION

The proposed device is a multi-functional biopotential acquisition and processing system, whose high-level block diagram is shown in Fig. 1. The focus of our work is the system-level design of the device, from the hardware development to the EMG-based gesture recognition application.

This device is composed of the multichannel Cerebro AFE [20], which is interfaced via SPI to an ARM microcontroller used for data acquisition and on-board gesture recognition SVM. This architecture combines the performance of a dedicated AFE with a general purpose microcontroller, leveraging

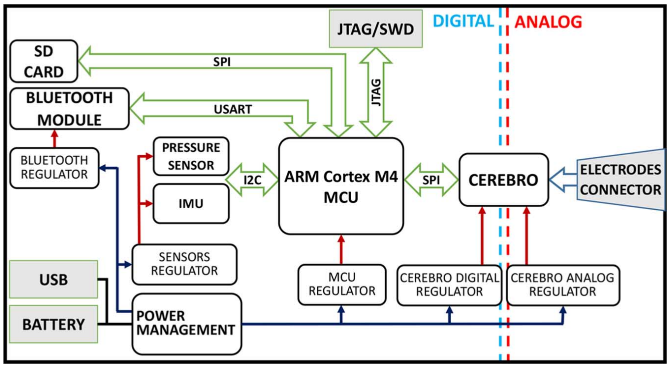


Fig. 1. Block diagram of the proposed device.

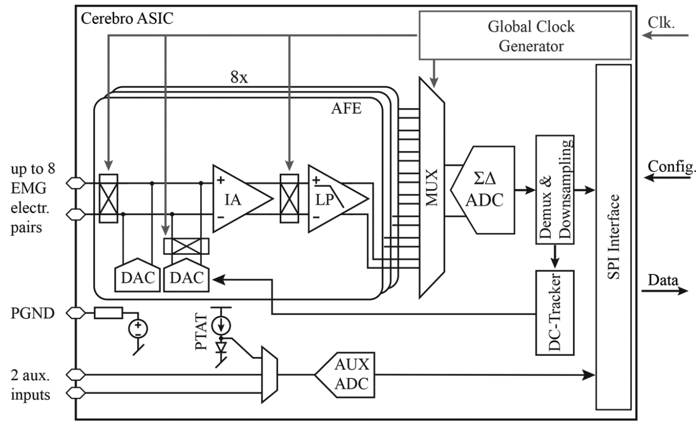


Fig. 2. Block diagram of the Cerebro ASIC [20].

system performance and flexibility for various biomedical applications. Additional inertial and pressure sensors have been added in order to enable in future developments sensor fusion techniques for an accurate gesture recognition and motion tracking. The acquired data and the resulting gestures can also be locally stored on a SD card or transmitted by a Bluetooth module to a host device. The raw data transmission is necessary for the training of the gesture recognition algorithm, resulting in the SVM models that are then uploaded and stored on the device for on-line use. We adopted a standard Bluetooth 2.1 module, since it allows to stream the acquired data at high rates and provides a reliable real-time acquisition system, which is not achievable using a Bluetooth Low Energy transceiver.

A. Signal Acquisition Front-End (Cerebro ASIC)

The task of an analog front-end (AFE) for biomedical-signals is to amplify the desired signal to an appropriate level for analog-to-digital conversion while suppressing all unwanted signals such as electrode DC-offset, mains interference and circuit noise. The Cerebro analog front-end depicted in Fig. 2 has eight differential data acquisition channels that are multiplexed for data conversion. Each channel consists of a variable-gain instrumentation amplifier (IA) followed by a first order active RC low-pass filter. The IA is chopper-stabilized to remove the flicker noise from the signal band. Measurements show 0.82 μV_{rms} noise in a 100 Hz bandwith [20]. Two current-mode digital-to-analog converters (DACs) compensate DC-offset at the IA input: the first DAC removes the input referred offset of the IA itself whereas the second, chopped DAC removes the differential input offset caused by the electrode-to-skin contact.

A single-loop 3rd order delta-sigma modulator with 3-level quantizer provides 80 dB of dynamic range for the accurate conversion of the eight input channels. Running at 16.384 MHz, the modulator is operated at an oversampling ratio of 64 with each channel sampled at 32 kS/s. A first comb filter decimation stage followed by a de-multiplexer and a second comb filter decimation and compensation stage provides 8 kS/s, 16 bit, high resolution sampled data at the AFE output.

Based on the decimated output samples of the ADC, the microcontroller controls the on-chip DC-tracker for each channel. When the DC-offset drifts above the linear voltage range at the input of the IA, the value sent back to the IA is incremented/decremented to compensate for the offset drift thereby closing the loop. The DAC DC-compensation values for each channel can be added to the corresponding received samples in the microcontroller to reconstruct the true DC signal acquired from the electrodes. This solution differs from the classical approach where a large external AC-coupling capacitor is used to create a system high-pass with a corner frequency below 1 Hz. With the implemented scheme, an effective dynamic range of 108 dB is achieved [20]. The Cerebro ASIC further contains a low-impedance patient ground (PGND) for setting the input common mode and a single-ended input, a 12-bit auxiliary ADC for internal temperature measurement or acquisition of an additional input.

B. System Level Design

The Cerebro AFE is interfaced with the ARM Cortex M4 microcontroller (STM32F407), which is responsible for data processing and controls the overall functionality of the board. Beside of a standard set of communication and control peripherals, this microcontroller is equipped with a Floating Point Unit (FPU) and a DSP instruction set, which allows it to efficiently process the acquired data and to implement the needed filtering and recognition algorithms. It runs at up to 168 MHz and it is equipped with 192 kB of RAM and 1 Mb of FLASH memory. This solution has been chosen to allow an advanced on-board processing of the data, delivering a 210 DMIPS performance with a 280 μA/MHz current consumption. Evaluating technical specifications, it results that a less powerful microcontroller (e.g., Cortex M3 or M0) would consume more energy due to the reduced instruction set and the absence of the FPU, whereas more advanced application-level processors (e.g., Cortex A) would increase the costs and energy consumption of the system.

The design of the printed circuit board (PCB) has been carefully implemented to maximize the signal integrity. The analog and digital circuitry has been separated and return paths of the signals have been kept as short as possible in order to reduce the inductive effects. The resulting assembled PCB is shown in Fig. 3. The board is designed on a 6 layers PCB with a single ground plane, a split power plane (separated analog and digital) and 2 signal layers (top and bottom). Discrete components are

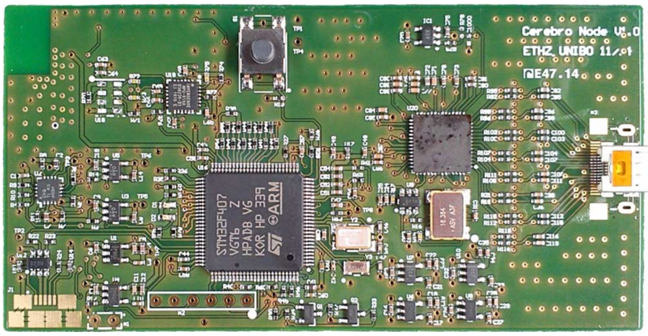


Fig. 3. Photo of the assembled PCB (top view). The dimension of the circuit is 85 × 50 mm.

TABLE II
SUMMARY OF THE PROPOSED SYSTEM

AFE:	
Aquisition channels:	8 EMG channels
Aquisition bandwidth:	1 kHz
Input-referred noise:	0.82 μV
Input range:	±300 mV
Power consumption:	15 mW
Microcontroller:	
Type:	ARM Cortex M4
Operating frequency:	168 MHz (210 DMIPS)
Flash:	1Mb
RAM:	192Kb
Maximum power cons.:	86 mW
Sleep mode power:	1.1 mW
Embedded platform:	
Dimensions:	85x50x6 mm
Total power cons.	29.7 mW

placed on both top and bottom layers in order to further reduce the resulting board size, which is 85 × 50 mm.

The supply of the system is handled by a dedicated IC equipped with an internal switching voltage regulator. This power management circuitry automatically detects the power source in use (battery or USB) and manages the recharging of the battery. Starting from this system supply, the different sections of the board (Bluetooth, sensors, analog) are provided with separate low-dropout voltage regulators. This flexible solution for controlling the power management improves the integrity of the acquired analog signals and allows us to switch-off or duty-cycle submodules of the board that are not required for a targeted biomedical application and thus enhancing battery lifetime. The main features of the device are summarized in Table II.

C. Data Acquisition and Pre-Processing

In this work, we showcase the potential of our system for the acquisition and processing of EMG signals for the recognition of hand gestures. The EMG signal is differential with zero mean and an amplitude varying from ±25 μV to ±10 mV, depending on the dimension and the depth of the muscles contracting underneath the electrodes. The acquired signal is a combination of the EMG potentials, a time-varying offset and noise, hence before gesture classification, the signal needs to be filtered and preprocessed.

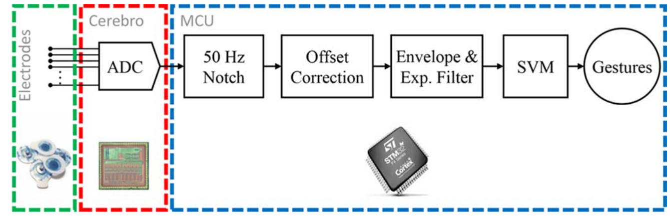


Fig. 4. Block diagram of the proposed system highlighting the different hardware components and the processing steps.

The processing chain is illustrated in Fig. 4 and its first step is the elimination of the power line interference, which is a sinusoidal component in the range 50–60 Hz, depending on the geographical location. It is caused by the AC frequency of the powerline and affects all the analog signals. Considering the nature of the EMG signals and the limited hardware resources, we choose to use a notch filter, which offers good performance at a very limited computational and memory cost. Thus, we implemented a second order notch filter with a Q-factor of 60.

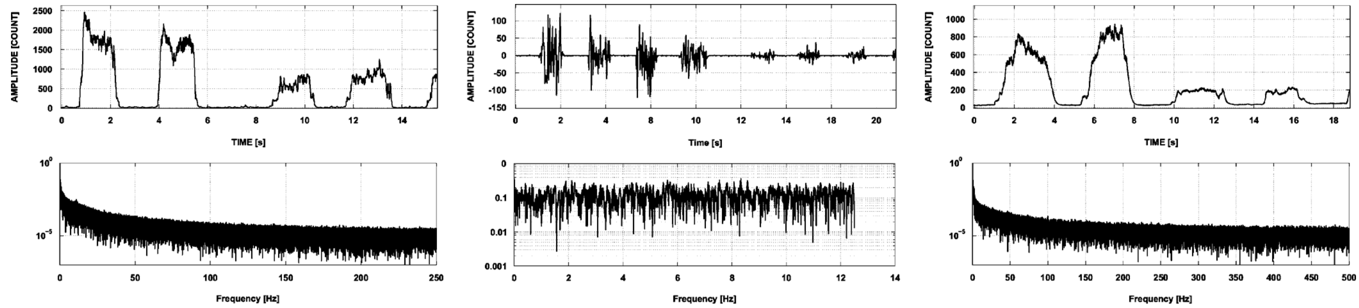
From the filtered differential signal an offset is removed when detected: it is estimated periodically by a moving average filter and removed from the signal. To obtain a single-ended signal we extract the envelope of the sampled differential signal, by replacing each sample with its absolute value. To eliminate high frequency noise, the signal is further low-pass filtered. This is achieved by a first-order filter: $y_n = \alpha y_{n-1} + (1-\alpha)x_n$, where x_n is the current sample and y_n and y_{n-1} are the current and the previous filtered samples. The coefficient α was set to 0.99.

This work extends a previous one [19] where we compared our signal quality with the one acquired with state-of-the-art active sensors [10]. Here, we complete the evaluation comparing our signal with the one provided by a recent wearable EMG system. In Fig. 5 we show the acquired EMG signal and its frequency spectrum for the three acquisition systems, (a) Ottobock active sensors, (b) MYO armband and (c) our device. The three signals were subsequently acquired from the same user, replicating the same acquisition setup for the three systems. The active sensors integrate a hardware amplifier, a low pass filter with a cut-off frequency of 450 Hz and extract the envelope of the signal. They provide an amplified signal in the range 0–3 V, which is directly acquired by the internal ADC of the microcontroller, with a sampling frequency of 500 Hz. The MYO provides a programming interface to receive EMG signals from its 8 sensors at approximately 25 Hz. We presume that internally the signals are amplified, filtered and sampled at a higher frequency, but no information is available yet.

Fig. 5 clarifies that the FFT extracted from the signals acquired with the Ottobock sensors and with our platform are equivalent, while the limited bandwidth provided by the MYO does not allow extraction of information in the frequency domain.

D. Gesture Recognition

As already mentioned, several techniques have been successfully used for EMG gesture recognition, with no clear winning approach. Having a resource constrained embedded system, we



(a) (b) (c)

Fig. 5. EMG signals (top) and their frequency spectrum (bottom) for the tested systems. (a) Ottobock. (b) MYO. (c) The proposed device. The signals represent gesture contractions and were acquired in sequence from the same user, placing the electrodes in the same position.

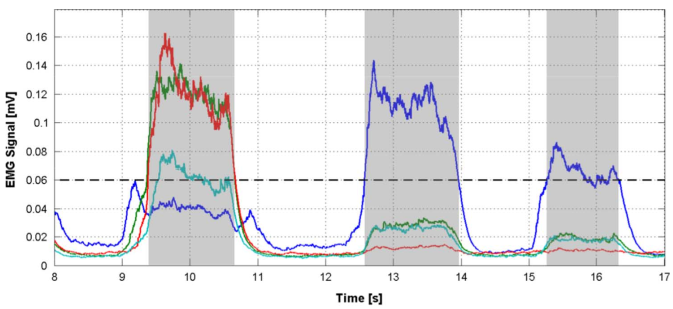


Fig. 6. Gesture segmentation: the threshold is plotted with the dashed line and the resulting gestures are highlighted in light gray.

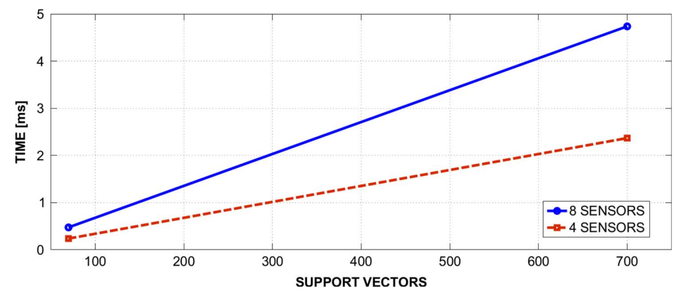


Fig. 7. Computation time for the online classification with SVM models of varying number of support vectors, as measured on the Cortex M4 MCU.

are interested in the best trade-off between classification accuracy and computational costs. Based on literature results [35], and our previous experience [6], [9], we decided to use a SVM for the classification of hand gestures. Since the SVM is a supervised learning classifier, we segmented and labeled the EMG collected data applying a threshold to detect when the gesture starts, as shown in Fig. 6.

The training of the SVM classifier is performed offline and produces a set of support vectors (SVs) used to discriminate the gestures to be recognized. The libSVM [36] is an open source library that can be compiled with GCC and provides the C or Matlab code for the training and for the classification with SVM. We performed the training stage offline on Matlab to create the SVM model. The resulting SVs are stored in the FLASH memory of the MCU and used for real-time classification. The dimension of each SV is equal to the dimension of the features vector used for the training of the classifier, which in our case is composed of the preprocessed EMG signals and it is equal to the number of acquired channels. At runtime, each new input vector is multiplied by a kernel function and its Euclidean distance from all the SVs in the model is evaluated. In this application, we used a Gaussian RBF kernel to cope with the variability of the EMG input signals. For the classification stage, we implemented an embedded version of the SVM classifier, adapting the libSVM to avoid the dynamic memory allocation that is not suitable for the limited resources of an embedded microcontroller.

The memory and computational footprints of the recognition algorithm are directly influenced by the number of support vectors in the trained model, which becomes an important evaluation factor for a resource-limited platform as ours. In particular, the time needed to classify a new instance is linearly proportional to the number of SVs in the model, as shown in Fig. 7, where the runtime computational time was measured on the MCU of the proposed system for 40 and 700 vectors respectively. Since SVs are stored as floating point vectors, if d is the dimension of the SVs and n is their number, the cost in memory of the classification algorithm is $4 \times d \times n$ Bytes. In our application, the maximum number of SVs obtained from the algorithm training is less than 300, which corresponds to 9600 Bytes and can be easily stored in the MCU's 1 Mb of FLASH memory.

IV. Experimental Results

The evaluation of the trade-off between the complexity of the system and its performance is a key element in the design of a wearable device. Firstly, we verified the setup of our platform to be confident that it is aligned with the SoA in terms of recognition accuracy. Hence, we made a detailed analysis of the system scalability in terms of the number of sensors used and recognized gestures, with relation to the computational and power costs. Finally, we acquired the EMG data from the MYO and we tested on them the accuracy of the same SVM algorithm implemented in our platform. All the data was acquired and tested on a PC using Matlab and an implementation of the SVM algorithm equivalent to the one we implemented for the embedded processor.

The EMG gesture data was acquired from four healthy subjects using the 8 fully differential channels of the Cerebro AFE at 1 KHz. The EMG electrodes were placed on the subjects' forearm as shown in Fig. 8. The set of 6 performed gestures was: power grip, precision grasp, open hand, pointed index and

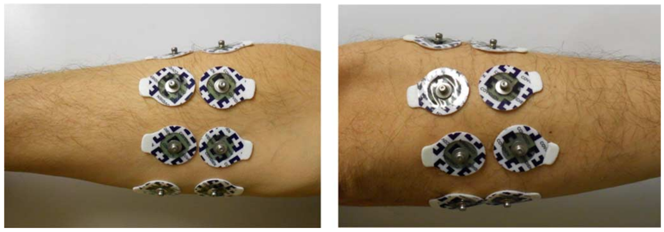


Fig. 8. The placement of EMG electrodes on the subjects' forearms.

the flexion/extension of the wrist. During the acquisition sessions, the subjects repeated each gesture 4 times, they maintained the gesture contractions for 3 seconds and separated each gesture with 3 seconds of hand relaxation (rest position). The final dataset is composed by 7 classes: the 6 gestures and the rest position. With the collected gestures, we trained an SMV model for each subject using 10% of the dataset, with the vector of acquired and pre-processed EMG channels as input. The recognition accuracy was computed applying the resulting SVMs to the continuous stream of acquired gestures, which was opportunely labelled. The average accuracy in the recognition of 7 gestures is 89.2% (with a maximum of 92%), with a model composed of 123 SVs. This value is comparable with the systems presented in literature and obtained with the high-end interface described in previous sections.

To better evaluate the interaction between the system complexity and the recognition capability, we tested the accuracy in the recognition of subsets of a varying number of gestures (from 4 to 7), using varying numbers of input channels (from 4 to 8). Starting from the acquired dataset, for each gesture and input channel dimension, we tested all the possible combinations of sensor configurations and of recognized gestures. The gesture recognition accuracy and the number of SVs in the trained models were used as performance metrics, to evaluate the precision and the computational costs for each case.

This analysis can provide a robust estimation of the system performance, eliminating the dependencies from the selection of a gesture set or from a subject-tuned sensor configuration that can modify the final accuracy of the whole system. The results are reported in Fig. 10, showing the averaged recognition accuracy (top) and number of SVs (bottom) for the different configurations. We can see that the accuracy increases slightly when number of sensors increases and gesture number decrease. The total difference in accuracy from 4 to 8 sensors is less than 2%. This trend is confirmed also by [27]. The SV number increases when the number of sensors decreases and this is mostly due to the difficulties of the SVM algorithm in the creation of the decision boundary caused by the reduction of the information contained in vectors.

Furthermore, for each combination of gestures, the configuration of the sensors that achieved the best accuracy was traced to verify if it is possible to find a pattern for the best sensor placement common for all subjects. Fig. 9 shows the occurrences of each sensor in the best accuracy configurations, for each subject involved in the experiment. A common pattern is not recognizable because the surface EMG electrodes collect crosstalk between near muscular fibers and the variability in the muscular structure requires a person-tuned setup.

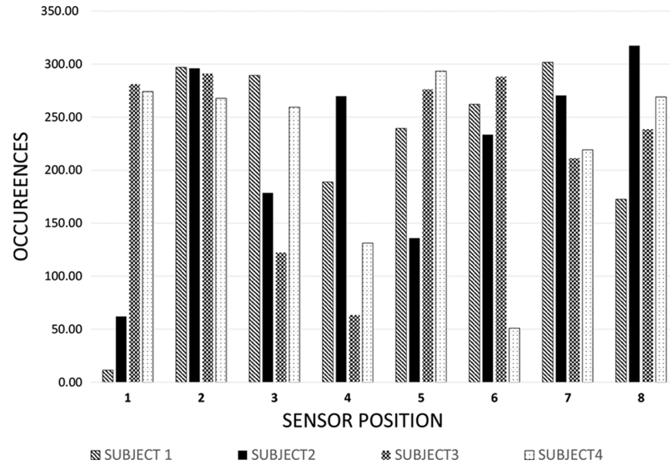


Fig. 9. Sensor occurrences in the configuration with the best accuracy for the subjects involved in the experiment.

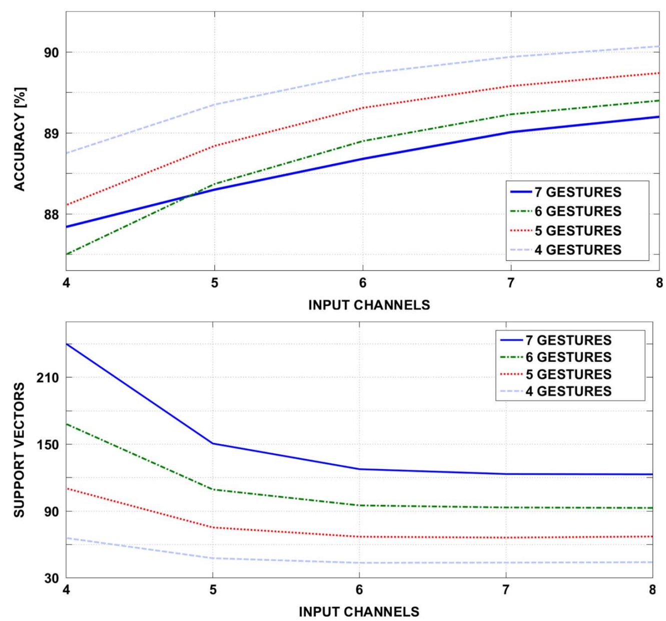


Fig. 10. Gesture recognition accuracy (top) and number of SVs (bottom) for varying numbers of input channels and recognized gestures. The reported curves are the average of the 4 users.

Using the collected data, we also characterized our system in terms of the signal frequency used for the SVM classification. The Cerebro AFE has a minimum sampling frequency of 1 KHz, hence the data is first acquired and pre-processed with that sampling rate. Then, we decimated the acquired samples, varying the sample rate from 25 to 1 KHz, to evaluate the impact of the data rate on the SVM classification. The result is presented in Fig. 11, where it is possible to notice that the average accuracy is not significantly affected by the data rate, while the number of SVs on the other hand is halved at 25 Hz, reducing considerably the computational time and power consumption. A lower sampling frequency cannot be used since the data pre-processing algorithm cannot be adapted for such low frequencies. An approach where the down-sampling is performed after the pre-processing did not bring significant improvement in power

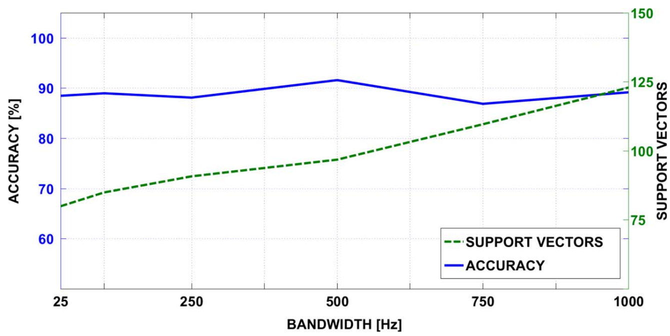


Fig. 11. Recognition accuracy and number of SVs for different SVM input sample rates.

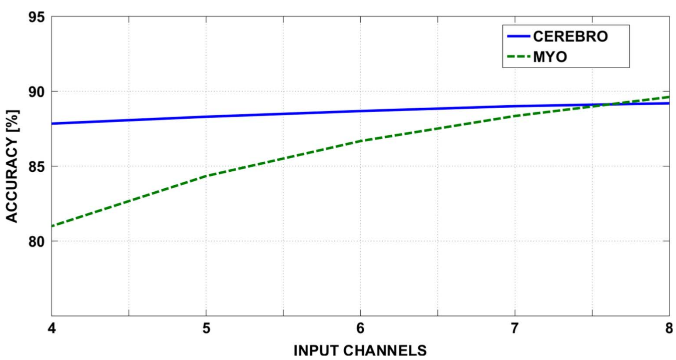


Fig. 12. Recognition accuracy of the SVM algorithm for different number of input channels, using EMG signals acquired with the MYO armband (dashed line) and our device (continuous line).

consumption since in this case most of the energy is spent to read data from the ADC.

To compare our system with the MYO armband, we used it to collect a dataset of gestures having the same characteristics described above. The only difference is that the output data rate of the 8 MYO channels is fixed at 25 Hz. There is no information on how this signal is acquired, but we suppose that the EMG signals are internally amplified and filtered by an analog circuit. To match this configuration, we sampled and pre-processed the EMG signals at 1 KHz and then downsampled the signal to 25 Hz. Both datasets were compared using the proposed SVM recognition algorithm, with the EMG signals as input, the first 10% of the gestures for training and the rest for testing. Fig. 12 shows the classification performance in the two cases for different numbers of signals used as input. As we can notice, with 8 sensors the accuracies are comparable, but the MYO system is less robust to the decreasing of sensors showing a drop of performance of 9.5% passing from 8 to 4 sensors compared to a drop of 1.5% for our solution. Moreover, our system is capable to perform the recognition algorithm on-board, while the MYO needs an external device on which to rely for the actual data processing.

An important feature of our system is its flexibility in terms of computational capabilities and power consumption. According to the application needs, it is indeed possible to configure different parameters, such as: the number of differential channels used, the number of detectable gestures, and whether to process data on-board or stream it through the Bluetooth interface. Bluetooth streaming allows to collect the EMG signals necessary

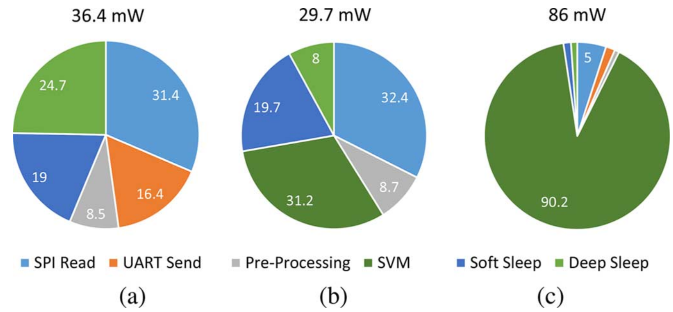


Fig. 13. Breakdown of the power consumption of the microcontroller for three different applications. (a) 8 channels data stream at 1 KHz. (b) 7 gestures recognition at 25 Hz. (c) 7 gestures recognition at 1 KHz.

for the SVM model creation during the training phase, which is performed on the PC. Once the model has been generated, it is transmitted back to the device and stored in the MCU's internal FLASH memory, turning off the radio to save power.

To analyze the power consumption of the proposed device, we partitioned the system into its three main components: the data acquisition interface, the microcontroller and the radio module. The power consumption of the Cerebro AFE is constant and it is equal to 15 mW. The average power consumption of the Bluetooth is proportional to the amount of data sent and can reach a maximum of 16 mW, when streaming 8 channels at 1 KHz. The power consumption of the microcontroller can be extremely variable according to the computational load, we thus analyzed the energy consumption during the 3 main phases of the program execution: data acquisition, computation and sleep.

During data acquisition from the AFE, the SPI interface, the interrupt controller and the DMA are active and used to transfer sampled data to the internal memory. The energy consumption is proportional to the number of used channels and the sampling rate, which for our application was 5.2 mW reading 8 channels at 1 KHz.

After acquisition, data gathered from the AFE is pre-processed with the digital filtering approach described in the previous section and this operation requires up to 0.7 mW. The classification algorithm requires much more power than the pre-processing step, in this case the power needed to classify data is affected mainly by the number of SVs and the number of used channels. In Fig. 13 we show the breakdown of the average power consumption of the microcontroller for three application scenarios: data streaming via Bluetooth, SVM classification at 1 KHz and at 25 Hz. When the desired computation is over, the microcontroller is programmed to go in a sleep state, which was chosen considering its power consumption and break-even time. The implemented deep sleep state has transition times of 13 μs and consumes only 1.1 mW.

In total, the power consumption of the device is influenced by the application and the system configuration. With 8 active channels, we found a 36.4 mW power consumption for the data streaming application at 1 KHz, 86 mW for SVM recognition of 7 gestures at 1 KHz and 29.7 mW for the recognition at 25 Hz. To lower the energy consumption it is thus possible either to reduce the sampling frequency or to reduce the number of detectable gestures.

V. Conclusion

In this paper, we presented a wearable device for EMG signal acquisition and processing, with an on-board real-time SVM algorithm for the classification of hand gestures. The system integrates Cerebro, an innovative AFE for the acquisition of biopotential signals, and an ARM Cortex microcontroller for efficient digital processing. Our work, adopting a multilevel design approach, ranges from the chip design of the AFE to device system-level design and integration. The optimized design of the analog ASIC provides a high quality in the acquisition of a wide range of biomedical signals, while the versatility of the microcontroller allows advanced on-board signal processing optimized for the application in use.

To validate the proposed system, we compared it with two different classes of EMG devices: high-end active sensors (Ottobock 13E200) and a low-cost wearable device (MYO). The first ones provide a high quality EMG signal and are used for medical and prosthetics applications, while the latter one is a recently introduced armband for EMG-based gesture recognition for interactive applications. Our device, combining the Cerebro AFE and digital signal processing, is capable to provide signals with the high quality comparable with the active sensors, while being low-cost, wearable and flexible.

We used the EMG signal for the classification of hand gestures and implemented on the microcontroller a real-time SVM recognition algorithm. With this approach we obtained a good classification accuracy of up to 92%, with limited computational costs of the algorithm.

The presented recognition approach allows scalability of the number of used channels and the high flexibility of the presented platform allows a versatile optimization for energy efficiency. While maintaining the recognition accuracy and the number of recognized gestures, we are able to scale the number of used channels and the algorithm frequency, thus saving energy and achieving a power consumption of 29.7 mW, fully compliant with the energy constraints of a wearable device. This platform reaches the same performance of the benchmark wearable system for natural gesture recognition, while adding onboard real time computing and reducing the cost of the whole system.

The next important challenge that we intend to face is the use of the device for clinical tests, taking advantage of its flexibility in terms of wearability and signal processing.

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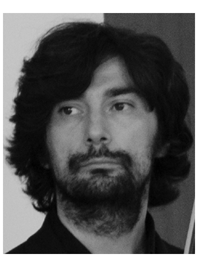

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