Smart Wearable Wristband for EMG based Gesture Recognition Powered by Solar Energy Harvester

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***Abstract*—With the recent improvement of flexible electronics, wearable systems are becoming more and more unobtrusive and comfortable, pervading fitness and health-care applications. Wearable devices allow non-invasive monitoring of vital signs and physiological parameters, enabling advanced Human Machine Interaction (HMI) as well. On the other hand, battery lifetime remains a challenge especially when they are equipped with bio-medical sensors and not used as simple data logger. In this paper, we present a flexible wristband for EMG gesture recognition, designed on a flexible Printed Circuit Board (PCB) strip and powered by a small form-factor flexible solar energy panel. The proposed wristband executes a Support Vector Machine (SVM) algorithm reaching 94.02 % accuracy in recognition of 5 hand gestures. The system targets healthcare and HMI applications, and can be used to monitor patients during rehabilitation from stroke and neural traumas as well as to enable a simple gesture control interface (e.g. for smartwatches). Experimental results show the accuracy achieved by the algorithm and the lifetime of the device. By virtue of the low power consumption of the proposed solution and the onboard processing that limits the radio activity, the wristband achieves more than 500 hours with a single 200 mAh battery, and perpetual work with a small-form factor flexible solar panel.**

I. Introduction

Recent advances in embedded systems, sensors, flexible electronics, and wireless communication have boosted the popularity of wearable technology, making smart objects (i.e. smart watches, smart glasses, etc.), fitness and health trackers highly demanded [1]. The commercial success of wearable devices has pushed the research and improvements of the electronics especially reducing the power consumption while increasing the computational performance. Pursuing smart systems to monitoring vital parameter and enable Body Area Network devices in a minimally unobtrusive fashion is a fundamental paradigm of next generation Internet of Things (IoT) ecosystem. In this scenario, printable and flexible technologies are increasing wearer comfort and even further to reduce the wearable devices form factor [2]. Nevertheless, market availability of these systems is still very limited mainly due to hard battery constraints and limited lifetime imposed by the required sizes and weights [3].

To improve the energy availability of the batteries, energy harvesting is a promising technique. Extracting energy from the environment [3] allows to supply devices or recharge batteries. Thermal, kinetic and solar system are the most popular ways to harvest energy and have been used to power wearable devices in recent research [3]–[6]. Flexible technology is providing novel photovoltaic panels that is making solar energy harvesting one of the most promising sources to power wearable devices [7]. Combining low power on-board processing platforms with flexible energy harvesting enables always worn self-sustainable smart sensors.

The clear trend is toward billions of long-lasting smart wearable devices in the so-called IoT wave. Besides the energy availability, another attractive challenge for industry and research is how and where to process the massive amount of data that these billions of devices are producing with their sensors. In fact, data needs to be processed to produce useful information for the users [1]. This vision holds the great promise to improve the health of patients, contributing to lower healthcare costs with a profound impact on the aging of the population as well.

Computational requirements of many commercial wearable systems allow to perform on-board only the extraction of sensors data and the processing of simple features. In fact, there are some commercial systems, like [8] or [9], with a battery life ranging from 6 months to one year. These devices leverage aggressive optimization strategies, as well as they benefit from the low power inertial sensors. However, biosignal processing of EMG recognition is still challenging since it requires heavier signal processing, complex hardware and power consumption [10], [11]. Recently, novel EMG-based gesture recognition systems [12], [13] have been presented in literature. However, such approaches are not suitable for extended battery lifetime due to lack of on-board processing capabilities or adequate power management. Execution of more demanding algorithms often require the connection with a host gateway, severely affecting the overall power budget of the system.

This paper presents a novel fully-flexible wearable device, achieving an unobtrusive self-sustaining smart system for EMG gesture recognition, designed on a flexible wristband and powered by a solar ultra-thin energy cell. Leveraging an array of passive EMG sensors, we designed a smart system capable to recognize directly on-board up to 5 hand gestures with 4 sensors located on the wrist. It achieves an accuracy of 94.02 % on the 5 classes/gestures. The solar harvester generates up to 16mW in outdoor scenario, enables a perpetual self-sustaining operation working with a duty-cycle of 3.25 % or extends the battery duration by 55 % in continuously working mode. The system demonstrates the feasibility of performing complex EMG signal processing even at low energy budget, achieving classification performance comparable with the State-of-the-Art (SoA) systems [14], [15], in a highly embedded platform suitable for wearable applications such as

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HMIs. To the best of our knowledge this is the first example of self-sustaining EMG-based smart wearable and flexible device.

The paper is organized as follows: Section II describes the system architecture in terms of hardware and firmware design, Section III presents the experimental results, describing the methods to minimize the power consumption while maintaining the classification accuracy and the lifetime estimation. Finally, Section IV concludes the paper.

II. Flexible Wearable System Architecture

Fig. 1 shows the proposed flexible bracelet with the three main blocks: the EMG sensor interface, the processing unit, and the energy harvesting subsystem. A low-power Arm Cortex M4F (Ambiq Apollo) Micro Controller Unit (MCU) is the core for data processing and classification. Finally, the top side of the bracelet is populated with flexible solar panels, while the harvesting circuits are used to both charge the battery and supply the whole system. All the blocks are finally mounted over a flexible Polyimide (PI) film PCB, which serves as a backing base for the copper layers on both sides of the bracelet. In the following sub-sections, details of the system will be further presented as well as the signal data processing techniques implemented on the embedded platform.

A. Flexible sensors and signal acquisition

As mentioned, the flexible bracelet has been implemented on a PI film that serves as a backing base for the inner and outer copper layers. The flexibility and low weight of this material offer the characteristics required for our system in addition to provide the structural support for the electronics, flexible solar panels and electrode array. The bracelet is designed to be placed on the wrist, offering a less intrusive system.

The EMG subsystem is placed on the bottom side of the wristband and it is composed of 15 auto-adhesive gel-based electrodes (i.e., 7 differential channels and reference), where the reference electrode is fixed at the head of the ulna bone. Moreover, a commercial Analog-to-Digital Converter (ADC) from TI (ADS1298) is used to sample the EMG signal.

The ADS1298, a 8-Channels, 24-bit delta-sigma ADC, designed for bio-medical applications [16], is responsible for the conditioning and sampling of the input electrodes' signal and it is connected to the microcontroller through Serial Peripheral Interface bus (SPI). The ADS1298 delivers flexibility through its high range of programmable configurations, essential during development steps.

B. Processing unit and data analysis

The low-power Ambiq Apollo ARM Cortex-M4F has been selected as microcontroller to process the data directly on the designed bracelet. This Integrated Circuit (IC) is the best ARM Cortex-M4F on the market in terms of low power and energy efficiency. In fact, its current consumption ranges from 0.8 mA in run mode to 419 nA in deep sleep mode with RAM retention. The maximum clock frequency is 24 MHz and it embeds 512 kB of flash memory and 64 KB of RAM. These features provide sufficient computational power to perform

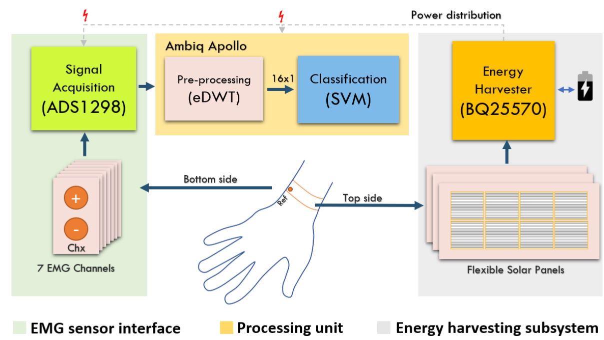

Fig. 1. Block diagram of the system.

the target application with the on-board gesture recognition algorithm.

The processing chain of a pattern recognition algorithm typically includes feature extraction [17]–[19] and classification [20], [21]. The most popular features for EMG pre-processing are: Energy of the Discrete Wavelet Transform (eDWT), Modified Mean Frequency (MMNF), Waveform Length (WL), Willison Amplitude (WA) and Root-Mean-Square (RMS), largely used in literature [22], [23]. Similarly, supervised classification algorithms such as Neural Networks (NN), SVM, Linear Discriminant Analysis (LDA) Classifier as well as Hidden Markov Models (HMM) [15], [24]–[26] reach accuracy levels above 90%, with computational complexity suitable for their execution on low power real time systems. As features extraction can affect significantly the performance of the classification, we investigated frequency and time domain features extraction techniques. In particular, RMS, WL, DWT, MMNF and a combination of DWT and WL were evaluated. Table I shows that the energy of the DWT outperforms the other features in terms of accuracy, thus, it was selected for the final application.

The DWT performs an efficient time-frequency analysis by decomposing the input signal in a bank of low pass and high pass filters to create a series of coefficients called Detailed Coefficients $(E_{D(n)})$. Our implementation relies on a 4-level decomposition over a window of 256 samples.

The gesture classification relies on SVM, a classification algorithm that leverages optimal accuracy with low complexity, essential for a real-time embedded application [27]. The SVM outperforms classifiers such as LDA in terms of accuracy while keeping computational complexity suitable for an embedded deployment. Algorithms such as NN will provide similar classification performance but at a higher computational cost. This has been already demonstrated in previous investigations [27] [28], thus, a further comparison has been omitted.

TABLE I
Accuracy values following the different features

Gestures	RMS	DWT	WL	MMNF	DWT+WL
Rest	98.34	98.77	99.13	89.06	98.88
H. Open	97.07	93.34	91.63	76.71	96.62
Pw. Grasp	84.83	93.59	72.53	61.97	86.86
Pronation	97.77	100.00	97.91	90.42	100.0
Supination	94.84	98.23	90.88	24.25	96.59
Avg.	**94.57**	**96.78**	**90.42**	**68.48**	**95.79**

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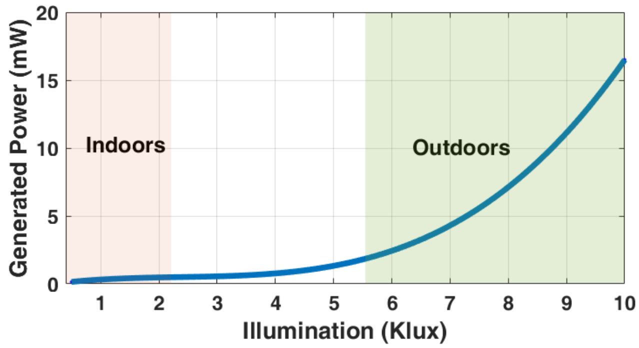

Fig. 2. Power generated in different illumination conditions.

Our implementation of the SVM is based on [29], a widely used library that supports multi-class classification. After empirical analysis, the Radial Basis Function (RBF) has been selected as the kernel of the classifier. The training and testing of the SVM is based on 3 datasets collected from different subjects. The final accuracy is calculated using 5-fold cross-validation.

The DWT and SVM codes were implemented in C language using CMSIS-DSP libraries provided by ARM [30] to minimize the number of cycles required to perform the necessary operations. In our final implementation, the memory footprint of the generated firmware is around 15 kB, entirely fitting the available resources.

In this preliminary version of the bracelet, the outputs of the classifier are displayed using 5 different LEDs placed on the board, although, the data (classification and raw data) can also be streamed via the UART ports of the MCU for debugging purposes.

C. Energy harvesting (EH).

As one of main goal of this work is to achieve a full flexible wearable device, thus, also the solar energy harvester needs to be flexible. The solar panel Power Film Solar SP3-12 [31] that uses AKAFLEX® technology from Kermpel employing a modified epoxy system characterized by temperature stability has been selected. This solar panel has a very small form-fact of only 1.2 cm x 6.4 cm that is ideal for our application. To convert efficiently the energy from the panel into the battery, we designed an EH subsystem circuit exploiting the SoA IC BQ25570 from Texas Instruments. The IC implements a Maximum Power Point Tracking (MPPT) circuit to maximize the conversion in all the light conditions. Due to the MPPT, the IC adapts the input impedance of the solar cells at run-time to maximize the energy transferred to the battery. An efficiency of around 90% is achieved during the conversion of energy. The EH subsystem provides also a high efficient buck converter that delivers a stable voltage output of 3.3 v supplying the whole system.

Experimental measurements indicate that the energy harvesting subsystem using a single flexible panel can provide up to 0.21 mW in indoor and up to 16 mW in outdoor scenarios. Fig 2 shows the extracted power for the different illumination conditions. More energy can be extracted by a bigger panel with the same technology, or a series/parallel configuration of single panels.

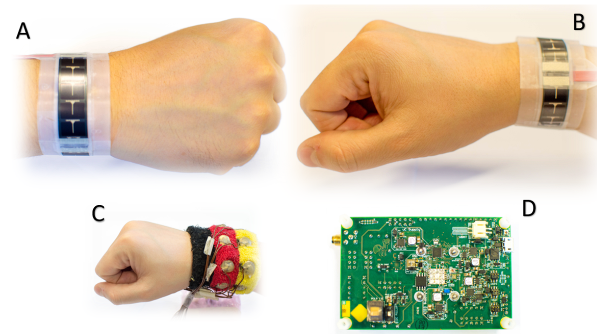

Fig. 3. Solar Harvester (A,B), Sensor Interface prototype (C) and Acquisition board (D).

III. Experimental Results

The system has been implemented and developed to test functionality, power consumption and battery lifetime.

For testing purpose, all of the three blocks were kept separated, as shown in Fig. 3, where A and B show the top and side view of the array of solar panels, C shows the array of electrodes and D presents the board including all the electronics. Future work will integrate all the layers in a single component. The system was tested on 3 subjects using a combination of DWT and SVM [24], achieving SoA accuracy while keeping a low power consumption.

A. Channel reduction and system validation

Since gesture number and sensor setup impact on computational requirements and battery life, a preliminary investigation on a setup with 7 electrodes connected to the ADC channels was performed to identify the best configuration and trade-off between number and position of the electrodes as well as between number of gestures and classification accuracy. On top of that, in this work we focus on 5 classes/gestures: rest position, hand open, power grasp, pronation and supination of the wrist. The number of gestures is suitable for a HMI control while the reduced number of EMG channels allows to optimize power consumption.

Table II shows the accuracy values obtained on 5 gestures with seven and four channels. The channel reduction decreases the energy consumption because of a minor number of channels used by the ADC converter and the less time spent from the MCU to process the data.

Using 4 channels the system achieved anyway high accuracy (up to 94 % with a minimal deterioration of the detection accuracy (<2.8 %)), simultaneously reducing the complexity of the pre-processing step without impact on the number of SVs required (97), gaining 4.1x in power efficiency.

In our experimental setup with 3 subjects, we attained similar accuracy values than in the previous test (94.02 %), comparable with the current SoA systems [14], [15].

TABLE II
Comparison of the performance after channel reduction

Gesture	Avg. Accuracy	S. Vectors
7 Channels	96.78	99
4 Channels	94.02	97

TABLE III
COMPARISON WITH SOA SYSTEMS FOR EMG CLASSIFICATION

Author	Sensor	Processing	Intrusive	Accuracy	Harvester	Bat. Life
[12]	EMG/Presure	PC, offline	YES	82	NO	ND
[32]	EMG/IMU	PC, online	NO	92	NO	ND
[33]	EMG/IMU	PC, online	NO	80-90	NO	24hrs.
This work	EMG	on-board, online	NO	94	YES	512hrs/perpetual.

B. Power consumption

Fig. 4 shows the power consumption of the MCU and the ADC. It is noteworthy that the power consumption is dominated by the ADS1298. The MCU is only responsible for 20% the required power due to the power management applied to the system.

Working at 24 Mhz and assuming a window frame of 256 ms, the MCU requires only 13 % of the time slot to process the data. When in idle, the MCU is put in a deep sleep mode. This process decreases the power consumption by a factor of 27.

Moreover, energy reduction can be performed by more aggressively duty cycling the system. We evaluated the system output when predicting 4 times the gesture every second (Full Mode) and a reduced duty cycling with 1 classification per second (Reduced mode). In this last mode, the average power consumption decrease to 1.27 mW. As demonstrated in [34] [35], using this mode, the system can be suitable for low latency applications such as external interfaces to control smart-phones or to provide biofeedback during stroke rehabilitation.

C. Toward self-sustainability

From our experimental results, the system operates for 129 hours (full mode) or 517 hrs (reduced mode) supplied by a 200mAh battery. Those results demonstrate the low power consumption of the proposed solution. Depending on the light conditions, harvesting can significantly extend the operation of the system and even achieve self-sustainability. In this work, we show preliminary promising results using a realistic estimation of the power generated from a small single flexible solar panel. From the previous session, under the assumption of 5000 lx is possible to harvest an average power of 1.825 mW. As a result, the solar harvester can extend the battery life up to 200 hrs for full mode, and work perpetually in reduced mode.

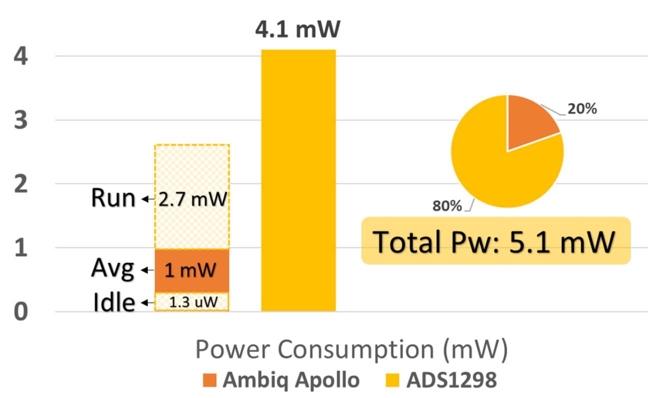

Fig. 4. Power consumption of the Ambiq Apollo with power management (left) and ADS1298 (right).

Table III presents a comparison between the proposed system and other approaches for wrist based EMG recognition. For completeness, we have also added the Myo armband [33] (originally designed to be worn in the arm). This commercial device performs gesture recognition using a PC, thus, it does not offer a fully wearable solution. Similarly, in [12], authors describe a system that is highly intrusive, where the classification also relies on a external device. In [32] authors have presented a classification system using EEG and EMU sensors but the processing is performed in a desktop computer, therefore, its embedded implementation cannot be guaranteed. To the best of our knowledge our system is the first attempt for a self-sustaining EMG-based device that is aligned with the SoA systems while considering the constraints posed by the current wearable technology, where battery duration plays an important role.

IV. CONCLUSIONS

In this work we presented a full-flexible low-power wristband which integrates all the required component for the detection of 5 hand gestures from 4 EMG sensors, and achieves 94.02 % accuracy. Our current implementation reaches comparable accuracy of other more energy hungry platforms presented in the recent literature. Furthermore, the system was endowed with a flexible solar panel enabling self-sustaining operation under the proposes assumptions. Future work will provide more experimental results on the self-sustaining system with a complete set of test in different application scenarios.

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