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Using Low-Power, Low-Cost IoT Processors in Clinical Biosignal Research: an In-depth Feasibility Check

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Abstract—**Research on biosignal (ExG) analysis is usually performed with expensive systems requiring connection with external computers for data processing. Consumer-grade low-cost wearable systems for bio-potential monitoring and embedded processing have been presented recently, but are not considered suitable for medical-grade analyses. This work presents a detailed quantitative comparative analysis of a recently presented fully-wearable low-power and low-cost platform (BioWolf) for ExG acquisition and embedded processing with two research-grade acquisition systems, namely, ANTNeuro (EEG) and the Noraxon DTS (EMG). Our preliminary results demonstrate that BioWolf offers competitive performance in terms of electrical properties and classification accuracy. This paper also highlights distinctive features of BioWolf, such as real-time embedded processing, improved wearability, and energy-efficiency, which allows devising new types of experiments and usage scenarios for medical-grade biosignal processing in research and future clinical studies.**

I. INTRODUCTION

Embedded wearable systems have gained a tremendous boost in popularity, prompted by the rise of unintrusive digital systems. In this trend, biopotential monitoring has profited significantly as newer portable devices allow extracting signal features, even in complex environments. Among the plethora of information available from the human body, neural activity in the form of Electroencephalography (EEG) continuously draws attention since it holds the promise to provide a direct brain-computer link [1]. Likewise, Electromyography (EMG) gesture recognition is a critical element to enable natural and advanced ways of communication and to monitor and diagnose muscular disease.

In the trend of extracting EEG and EMG biomarkers, several low-cost platforms (<2k EUR), such as Emotiv Insight and EPOC+, Neurosky MindWave, and OpenBCI, have recently emerged [2]. For instance, Emotive offers a range of headset devices from 2 to 32 channels to automatically detect some events such as facial expressions, emotional states, and mental commands. OpenBCI is a low-cost open-source platform that offers solutions for biosensing. It has recently gained great popularity as it provides hardware-software solutions while allowing access to raw data directly without extra costs. However, the research community still relies heavily on widely validated devices to ensure trustworthy results and to retain academic confidence.

From the companies providing research devices, g.tec, ANTNeuro, and Noraxon have a notable share in research

usage. For instance, Nautilus from g.tec consists of a wearable headset (8-32 dry/wet EEG electrodes @ 24bit/500SPS) to record brain activity in clinical environments for up to 10 hours. eego^{TM}mylab from ANTNeuro (EEG) has also been included in several research projects with notable results [3], [4]. It is available in four different versions and can be cascaded to obtain up to 256 channels to allow high-density EEG analysis. When streaming data, it offers a battery life of up to 5 hours. Likewise, Noraxon DTS is used in EMG research with considerable success [5], [6]. The system consists of several EMG nodes connected wirelessly to a base station, which reduces the intrusiveness of the system considerably. The lead of the previously introduced devices is commonly associated with two factors, including the excellent electrical characteristics of the equipment and the overall robustness of the headsets. Nevertheless, these systems do not provide highly embedded hardware, that might limit the portability and wearability for out-of-the lab experiments. Furthermore, they are highly expensive (then of thousand of EUR), which severely limits research opportunities.

In previous work, BioWolf has been recently introduced [7] as a highly-wearable platform for BCIs and medical-grade IoT applications, which addresses not only raw data streaming but also the in-situ digital processing challenge. The device includes a commercial 8-channel analog-front-end (AFE) for medical-grade ExG signal acquisition and a programmable parallel ultra-low-power processor for advanced DSP [8]. The system aims at "extremely wearable", smaller-than-watch scenarios (e.g., patches, behind the ear setups, rings, buttons). Thus, besides providing state-of-the-art (SoA) performance for HMI and biosignal sensing [9], this device offers many other features while also being portable and inexpensive[1].

The goal of this paper is thus to present a quantitative analysis of the signal acquisition and processing of BioWolf (ExG) and two research-grade acquisition systems, namely, ANTNeuro (EEG) and the Noraxon DTS (EMG). Specifically, in this paper, we present an electrical characterization of all three systems, and additionally, we offer a systemic comparison through a quantitative analysis of EMG and EEG (SSVEP) classification.

The preliminary results presented in this paper demonstrate that BioWolf not only meets the International Federation of Clinical Neurophysiology (IFCN) standards [10] but also provides electrical characteristics in line with the research devices included in this study. In terms of EMG classification performance, our tests performed with a single subject suggest that BioWolf and Noraxon DTS perform almost identically (97-98% accuracy). When comparing EEG the classification performance, initial results indicate that BioWolf provides a classification accuracy improvement of 11% to

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[1] Without considering Mr. Wolf SoC, the device estimated volume price is about 200 EUR. A commercial PULP chip fabricated in similar technology as Biowolf (with less advanced features) adds 1-5 EUR.
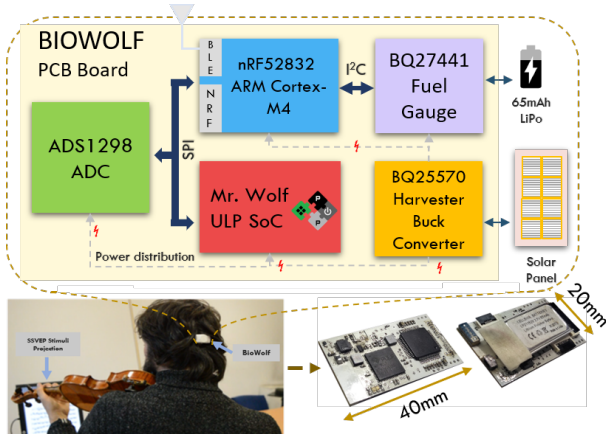
Fig. 1. BioWolf block diagram including the PCB implementation and an usage example.

eego^{TM}mylab. Finally, this paper also explores the benefits of the onboard, real-time processing by implementing the processing chains (EMG and EEG) on Mr. Wolf, which allows for up to 2.4x in energy savings to raw data streaming.

These first results show that BioWolf delivers research-grade performance while in a robust, energy-efficient, and unintrusive platform that can potentially open the prospect of implementing biosignal monitoring even in more challenging scenarios while achieving SoA performance.

The paper is organized as follows. Section II introduces the material and methods. In section III, we introduce the results of the electrical characterization of all the devices and the classification performance obtained. In this section, we also showcase the benefits of the onboard and embedded processing through Mr. Wolf. Finally, in sections IV and V, we offer a discussion and draw some conclusions, respectively.

II. MATERIAL AND METHODS

A. Devices under test (DUT)

1) BioWolf: BioWolf features three main components, a parallel ultra-low-power System-on-Chip (SoC) microcontroller unit (MCU) for signal processing, a Nordic ARM-SoC MCU for Bluetooth Low Energy (BLE) communications and system management, and an AFE for bio-signal acquisition. The system also incorporates a nano-power buck-boost regulator for energy harvesting, a fuel gauge to check the battery state, and an electrode impedance tracker subsystem to check the quality of the electrode contact.

The biosignal acquisition subsystem is based on the ADS1298, a commercial AFE from Texas Instruments, currently considered a standard for biopotential acquisition platforms due to its favorable trade-off between performance and power consumption. The AFE allows simultaneous sampling of up to eight bipolar channels, at up to 32 kbps sampling rate and 24-bit resolution. The computational core is based on Mr. Wolf, a multi-core programmable SoC implemented in TSMC 40 nm CMOS technology, combining nine RISC-V processors and a complete set of peripherals (JTAG, SPI, UART, and GPIOs). Fig. 1 shows a block diagram of the complete system, the PCB implementation, and an application for SSVEP-based BCI.

2) Noraxon Acquisition System: The Noraxon acquisition system includes two main modules, i.e., the wireless EMG probes, and the receiver (Desktop DTS). The probes can sample data at various rates (1-4SPS) at a resolution of 16bits. Signal gain can be adjusted from 200 to 500x. The node weight is about 14gr and provides up to eight hours of continuous acquisition. All available raw data is

transmitted wirelessly to the Desktop DTS (receiver), where all the channels are synchronized (up to eight). Data can be visualized in real-time during experimentation through a USB connection to a PC.

3) ANTNeuro eego^{TM}mylab: eego^{TM}mylab is a multichannel EEG acquisition system featuring 32 to 256 EEG channels (in cascade mode) at a resolution of 24bits that can be sampled at up to 16kHz. The system also allows for a trigger input and programmable gain. The system is fully portable, being powered by both external DC and battery. When battery-powered, the system provides up to 5hs of continuous operation. The amplifier has a dimension of 160x205x22mm and weights <500gr. The acquired data is available through a USB output interface. Table I shows a summary of the features of all DUTs.

B. Electrical Tests

To asses the performance of the devices from the electrical standpoint, in this work, we have focused on three main IFCN parameters, including the Input-referred noise (IRN), Common Mode Rejection Ratio (CMRR), and, Channel Interference (CI). IRN, measured on the 0.5-100Hz bandwidth, is calculated by applying a short circuit between the positive and reference electrodes. These are also connected to an external circuit simulating the skin-electrode contact impedance (51 kOhm||47nF). The CMRR is measured by injecting a sinusoidal signal to both positive and reference channels to measure the rejection ration of the OA. The frequencies employed are 40Hz, 80Hz, and 120Hz. The channel interference is measured by injecting a signal to a given channel and measuring the interference introduced to an adjacent channel.

C. Classification tests

To provide a complete evaluation of the performance of the systems for a specific application, we have also studied the performance obtained through the classification of EMG and EEG signals using the classification mechanisms presented in the following.

1) EMG classification: The processing chain of a pattern recognition algorithm typically requires feature extraction and classification [11]. In this work, feature extraction comprises extracting the Waveform Length (WL) of the signal and the gesture classification relies on SVM, a classification algorithm that leverages optimal accuracy with low complexity, essential for a real-time embedded application [12]. Our SVM implementation is based on [13], a widely used library that supports multi-class classification.

2) EEG classification: To evaluate the performance of the EEG classification, we have targeted the classification of SSVEP signals, which consist of brain response to periodic stimuli. The signal processing and classification is based on the canonical correlation analysis (CCA) [7], which calculates the *canonical coefficients*, i.e., the maximal correlation

TABLE I
ADVERTISED FEATURES OF THE DUTs

Characteristics	Noraxon	eego mylab	Mr. Wolf
Signal Target	EMG	EEG	ExG[1]
N. Channels	8	32-256	8
Portable	yes	yes	yes
Resolution	16bits	24bits	24bits
Battery life[2]	8	5	9
Size	34x24	160x205	40x20
Gain	200-500	NS	12
Connectivity	Wireless[3]	USB	Wireless (BLE)

[1] Commonly used for EEG, EMG and ECG.
[2] When streaming raw data.
[3] Protocol not specified.

between to sets of multidimensional variables. Classification is performed using a threshold over the result obtained from computing the Euclidean norm of the canonical coefficients. As a complementary experiment, we have also measured, using Power Spectral Density (PSD), the alpha waves response during the closure of the eyes. Fig. 2 summarizes the DSP chain for both EMG and EEG classification. All tests performed in this work have been approved by the bioethics committee of the University of Bologna.

D. Real-time embedded processing with BioWolf

The systems presented previously allow only for data sampling, visualization, and logging for offline data analysis. BioWolf, on the other hand, allows onboard and real-time DSP. To showcase the performance of the system, we included two performance parameters, *computational complexity*, and *battery life*, measured through the embedded implementation for the EMG and SSVEP classification. The computational complexity is measured as the number of CPU cycles required to finish a classification task. Battery life, measured in hours, provides the overall efficiency of the system, which can be affected by several factors, including latency, computational complexity, firmware optimizations, and SoC technology.

III. RESULTS

A. Electrical Comparison

All DUT have been analyzed in terms of the electrical test introduced in II-B. Table II summarizes all the results of the electrical tests. The results in IRN denote that all systems generate noise above 6uVpp. In terms of V_{RMS}, eego^{TM}mylab provides the lowest noise, closely followed by BioWolf. CMRR for all devices is above the recommended 120dB, with the ANTNeuro eego^{TM}mylab producing the highest CMRR ($>$160dB). It is noticeable that the results remained stable for all tested frequencies. Finally, the CI for all DUTs is above 150dB, with the Noraxon DTS denoting the highest values (161dB).

B. EMG Gesture Recognition: BioWolf vs Noraxon

Aside from testing the electrical parameters of the DUTs, we have also performed a comparison between BioWolf with the Noraxon DTS for EMG gesture recognition, allowing us to provide a more systemic comparison between the devices. For this, a single subject using eight-bipolar electrodes placed at the forearm in a ring configuration, performed nine (8 + rest) typical hand gestures compatible with HMI. Since the signal acquisition was not performed simultaneously, three trials ware carried to reduce the bias of the experiment. The signal processing employed to classify the signals is denoted in section II-C1.
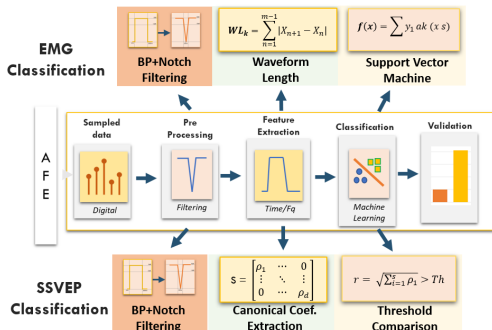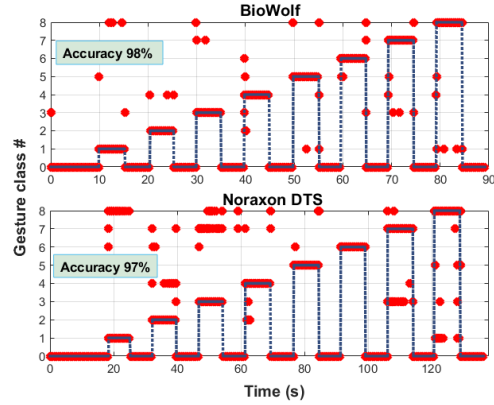

Fig. 3. Gesture recognition classification output

Fig. 3 presents the classification output of a complete trial, indicating in blue lines, the original data label and in red the SVM classification points. It is noticeable that there is a steady classification for both devices (similar for all trials), which is confirmed by the classification accuracy measured (average) in 98% for BioWolf and 97% for Noraxon DTS.

C. EEG tests: BioWolf vs eego^{TM}mylab

To asses the performance of BioWolf to eego^{TM}mylab, two tests were performed. The first, an alpha wave test, performed using a single electrode, located around the forehead (Fpz), with reference and GND at A1 and A2, respectively. On a 2-trial session, a single subject was instructed to close the eyes to elicit alpha waves. Fig. 5 show the results obtained, where two details are evident. First, the magnitude (linear) is up to 2.5x bigger for BioWolf, and second, the overall noise outside the band is lower BioWolf, which results in an SNR improvement of 4dB. The second test involves experimentation with SSVEPs. The testing included four frequencies ([5 6.2 7.4 8.6]) presented for 10s each through a computer screen employing the sampled sinusoidal stimulation method [14]. The experimental setup consists of a single electrode located at Pz, with reference and GND at A1 and A2, respectively. The DSP of the elicited EEG signals is detailed in section II-C2. Fig. 4 depicts the CCA response for the different target frequencies, where it is noticeable that BioWolf provides higher correlation values for each stimulus, which is confirmed when evaluating the classification performance. Using a mean-based threshold for classification, the EEG from BioWolf provides up to 72% in classification to 61% from eego^{TM}mylab, an 11% performance increase.

D. Embedded classification with BioWolf

To fully showcase all the features of BioWolf, we have also implemented the complete processing chain of the EMG
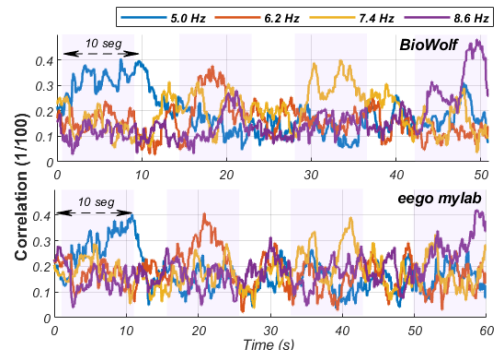

Fig. 2. EMG Gesture Recognition and SSVEP DSP and classification block diagram

Fig. 4. SSVEP classification output for BioWolf and eego^{TM}mylab

TABLE II
ELECTRICAL TEST RESULTS

DUT	IRN		CMRR(dB)			CI (dB)
	Peak-to-Peak(uVpp)	RMS(uV)	40Hz	80Hz	120Hz	
BioWolf (G=12)	3.90	0.40	127	127	127	151
Noraxon DTS	5.97	0.69	144	143	144	161
eego ^{TM}mylab	3.95	0.36	166	165	165	152

and SSVEP processing presented in section II-C. Thanks to the Mr. Wolf SoC that enables parallel processing of the operations, the EMG gesture recognition can be completed in 74k cycles, with a latency of 25ms/classification, allowing for up to 23h of battery life. The processing and classification of the SSVEPs require 94k cycles, which provides a battery life of 22h when setting 25ms of latency. The local processing thus allows for at least 2.4x energy savings with respect to direct data streaming for offline or external processing.

IV. DISCUSSION

The results obtained denote that BioWolf not only is in line with the IFCN standards but also provides similar performance to the research-grade systems analyzed. The IRN values obtained demonstrate BioWolf shares a similar noise to the other systems for both peak-to-peak and RMS noise. CMRR is in all cases above the recommended value of 110dB, with the eego^{TM}mylab providing the highest rejection ratio. The electrical characterization results obtained were also complemented by experiments on end-to-end biosignal processing applications. The accuracy of the EMG classification of BioWolf and Noraxon DTS is comparable, without significant differences (1% improvement for BioWolf). Regarding the more challenging EEG signal, the tests conducted denote that BioWolf allows for an 11% improvement for the classification of SSVEP signals with respect to eego^{TM}mylab. We have also demonstrated that BioWolf can perform both EMG and EEG classification in real-time at a power budget that allows for more than 22h of operation, providing 4.4x, 2.75x, and 2.44x improvement with respect to Noraxon, eego^{TM}mylab and BioWolf itself when in streaming mode, respectively. This battery life boost is the result of embedded processing and parallel computing available thanks to Mr. Wolf SoC. It is also to note that BioWolf offers significant improvements to current experimental sensor nodes for biosignal acquisition and processing, as highlighted in [7], allowing advanced algorithms to run efficiently in a non-intrusive device form-factor. When considering system costs, the proposed architecture has an estimated price lower than 200 EUR, a significant reduction, even after market markup, with respect to the commercial devices used in the comparative experiments. Lower cost implies enhanced opportunities for large-cohorts studies and experimental testbeds.

The results described in this paper outline a clear trend. Still, this work holds some limitations when delivering definitive results as it is restricted to the study of a single subject. Nevertheless, the methodology presented here will serve as a tool for future work to include an extended number of subjects. Similarly, and although this work aimed to validate BioWolf and showcase its features, future work will also include other commercial and research acquisition devices to provide a complete picture of the new trend for portable biosignal monitoring.

V. CONCLUSIONS

This work presented a preliminary assessment of the features and performance of BioWolf and two SoA devices for EMG and EEG signal acquisition. The comparison includes electrical tests and end-to-end biosignal classification application tests. The results obtained denote that BioWolf achieves similar performance (slightly better) at a lower cost while also providing embedded capabilities for extensive experimentation and real-time processing in an unintrusive, versatile, and energy-efficient platform.

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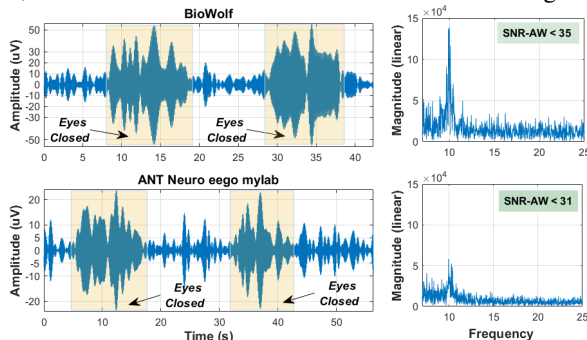
Fig. 5. Alpha waves test