A Surface Electromyography-Based Platform for the Evaluation of Sarcopenia

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Abstract— **Sarcopenia is a disorder characterized by a loss of muscle mass and muscle strength. It is associated with the natural ageing process, as well as geriatric medical conditions and bed rest. Consequently, it is very beneficial from a medical point of view to periodically monitor patients at risk of developing sarcopenia to early detect its onset or progression through objective and specific indicators. In the last years, surface electromyography (sEMG) increasingly plays an important role for prevention, diagnosis, and rehabilitation in this research area. Moreover, the recent progresses in EMG technologies have allowed for the development of low invasive and reliable smart EMG-based wearable device. The paper presents the design and implementation of an integrated platform that includes a sEMG based wearable device and interfacing with a processing software for clinical monitoring and management of the pathology. The system has been designed to both preventive (early diagnosis) and monitoring purposes of the patient's condition over time. Here, we present a preliminary study on the feasibility of the developed platform for management of sarcopenia. Specifically, this work deals with the identification of the best trade-off between sampling frequency of the EMG signals and variance of the highly discriminative features extracted within the EMG signals for the automatic measurement of sarcopenia.**

Keywords- wearable device; EMG; Sarcopenia; Ambient Assisted Living; Ageing Adults.

I. INTRODUCTION AND RELATED WORKS

A serious change associated with aging is the progressive decline in muscle mass, a downward spiral that can lead to reduced strength and function. In 1989, Rosenberg proposed the term 'sarcopenia' to describe this age-related reduction in muscle mass [1]. Although sarcopenia is primarily a disease of the ageing adults, its development may be associated with conditions that are not exclusively seen in older persons, but it can also be seen in younger patients, such as those with inflammatory diseases [2]. In sarcopenia, the loss of muscle mass and the consequent loss of strength are also accompanied by a decreased function of the muscles. In general, sarcopenia produces a deterioration in physical functions and means postural instability, alterations of thermoregulation (increased mortality in summer or in extreme winter), worse bone trophism (lack of stimulation of contraction), modification of glucose homeostasis (lack of storage and consumption) and reduction of basal energy production. With the passing of the years of life of a standard subject, the loss of muscle mass progresses in step with the loss of muscle strength, which can be of the same proportions or even greater. By age 50, many people have already lost around 10% of their muscle mass and by age 70 they will have lost around 70%.

Generally, sarcopenia is very difficult to treat because it is not easy to evaluate the temporal trend of its three fundamental components, which are: 1) muscle strength, 2) muscle mass, 3) physical performance such as walking speed. In the current state of the art, the three components mentioned above are evaluated with different non-invasive gold standard techniques, such as Computed Tomography (CT), Dual energy X-ray Absorptiometry (DXA) or Magnetic resonance Imaging (MRI) [3][4]. But all the aforementioned exams are rarely used in practice due to lack of portability and high equipment costs. Moreover, their use requires highly trained medical personnel.

In the last years, smart technologies such as wearable devices, mobile apps and embedded systems are frequently discussed in the healthcare field and without doubt the use of enabling hardware and software technologies will play a crucial role in the creation of innovative and unobtrusive Ambient Assisted Living (AAL) systems that can support for early diagnosis and monitoring of patients affected by sarcopenia. Surface EMG (sEMG) is an important non-invasive measurement for monitoring muscle fatigue among the physiological measurement systems. EMG signals are the electrical activity produced by the muscle's motor units during their contractions. The sEMG measurement method is safer and less invasive than the intramuscular technique and it presents good performance in the muscle action potentials monitoring. It uses noninvasive, skin surface electrodes, realized with pre-gelled, textile or hydrogel materials, located near the muscles of interest [5]. Several works in literature have focused the attention on the use of the EMG signals in medical context [6]. For example, in [7][8] different applications of EMG-driven muscle models for determining muscle forces in the ankle, knee, back, and upper limb, for normal and pathological conditions were described. In [9] the authors developed an EMG patch, which could be worn on the lower leg, the gastrocnemius muscle, to detect real-time muscle fatigue while exercising. Kuthe et al. [10] quantified muscle strength based on force generated by the muscle during isometric contraction and the muscle fatigue using sEMG. Yu et al. [11] developed a wireless medical sensor measurement system, inclusive of EMG, motion detection, and muscle strength, to detect fatigue in multiple sclerosis patients.

As highlighted by the brief state of the art introduced, sEMG is widely used for the analysis of specific pathologies

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but very few works in literature have focused their attention on the use of sEMG for monitoring/evaluating sarcopenia.

Consequently, the aim of the proposed work is to develop a novel platform that integrates smart sEMG technology and a software to provide a decision support tool to healthcare personnel. The platform has been included in a first validation in a research laboratory aimed to demonstrate the sensors performance and the system effectiveness.

The paper is structured as follows. Section II describes materials and methods that have been used in this study, providing an overview of the system architecture, and detailing the algorithmic steps of the proposed pipeline. Section III presents some experiments carried out to evaluate the best trade-off between sampling frequency of the acquired signals and variance of the obtained feature values. Finally, section IV draws some conclusions and final remarks.

II. MATERIAL AND METHODS

The overall system is compound of two main components, a hardware device capable of detecting all sarcopenia-related parameters and a software component capable of processing the data coming from the hardware component (sEMG), storing them, and making them available to the end user.

To acquire data, the sEMG sensors were located on the Gastrocnemius Lateralis and Tibilias Anterior muscles. They were placed along the approximated direction of muscle fibers, with the inter electrode distance of about 20mm to obtain the maximal surface EMG amplitude. The electrodes for Tibialis muscles were applied at about 1/3 of the distance between the tip of the fibula and the tip of the medial malleolus. As for Gastrocnemius, the electrodes were placed at about 1/3 of the line head of fibula on the most prominent bulge of the muscle. To increase the stability of the probes and to reduce the movement artifacts, each sensor was held in place by an elastic band. A representation of the proposed EMG-based platform for the measurement and management of Sarcopenia is shown in Figure 1.

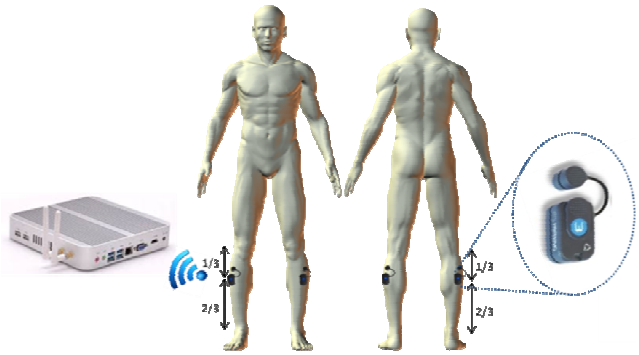

Figure 1. Overview of the proposed EMG-based platform for the measurement and management of sarcopenia.

The hardware setup has been developed by using the wearable sEMG system FREEEMG1000, produced by the BTS Bioengineering [12].

The system is made up of a USB receiver and up to 10 wireless EMG probes. The considered sensors are minimally invasive: no wire is used, dimensions are 41.5 × 24.8 × 14 mm, and the weight is about 10 gr. They are attached to the common pre-gelled electrodes by using clips, allowing a fast, simple, and robust mounting for the user's movements at the highest level of usability.

The probes integrate the active electrodes, which reduce the noise and an on-board solid-state buffer memory system, which guarantees the data safety in case of signal loss during the acquisition. The range of the wireless data transmission is about 20 meters in free space, according to the IEEE802.15.4 protocol. It is possible to acquire the data for more than 8 hours in streaming mode, through the rechargeable lithium-ion integrated batteries. The sampling rate of up to 1000 Hz and the 16-bit resolution permits a high degree of accuracy.

The real-time application has been realized using Microsoft C# language (Figure 2). In the design of the interface, it was considered that it can be used by medical operators and consequently it is as user friendly as possible. The main functions offered are: 1) display of the connection status of the probes (and relative battery life), 2) entry of the end-user fiscal code in order to associate the acquisition session with the user, 3) setting, pairing of the probes, 4) graphic display of the trend of the raw signals 5) start and stop of acquisition for any sub-sessions, 6) buttons for feature processing and possible sending of data (structured via REST/JSON messages) to external processes.

Figure 2. Interface of the software developed for the acquisition of raw EMG signals, data elaboration and sending to external processes.

The algorithmic framework for the acquisition and elaboration of the EMG signals is on an embedded PC, which receives the data through the compact (dimensions 82 × 44 × 22.5 mm, weight 80gr), wireless and USB interfaced receiver. The evaluation of muscle strength from a raw EMG signal generally follows three basic procedures: (1) continuous sample acquisition; (2) signal pre-processing, (e.g., filtering and/or normalization); (3) feature extraction, i.e., selection of relevant parameters for the specific application context. Some details of the implemented algorithmic pipeline (Figure 3) are reported in the next subsections.

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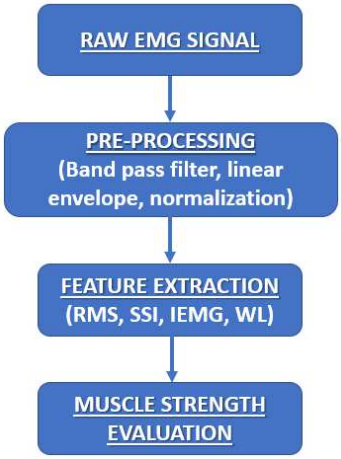

Figure 3. Representation with a logical block of the implemented pipeline for measurement and management of sarcopenia.

A. *Pre-processing*

The raw EMG signal acquired from each probe is subject to a pre-processing algorithmic stage to reduce the disturbances caused by movement artifacts and environment noise. In the present work this is achieved through the application of a bandpass filter within a frequency range of 20–450 Hz. Moreover, for EMG-tension comparison, the signals are processed by generating their full wave rectification and their linear envelope [13]. This was carried out with the use of 10th order low-pass Butterworth filter, with a cut-off frequency of 10 Hz. An example of sEMG signal emitted from a single probe (a) before and (b) after the pre-processing step is depicted in Figure 4.

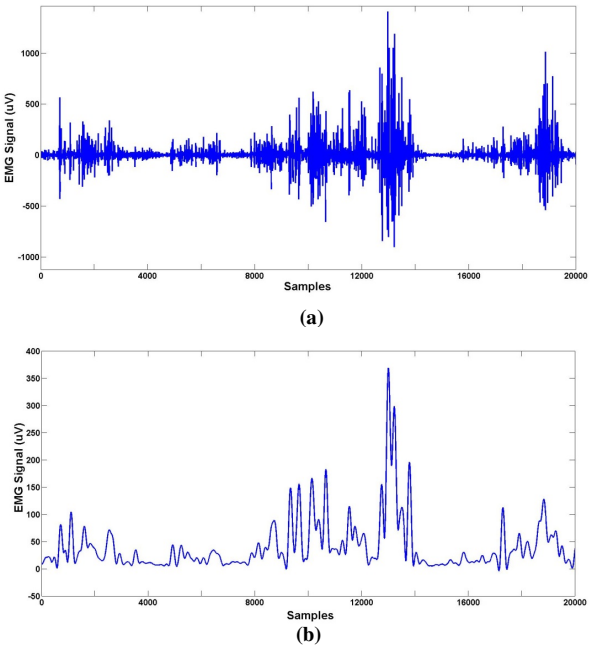

Figure 4. (a) An example of raw EMG signal. (b) EMG signal after pre-processing step.

Before the evaluation of muscle strength, to increase the objectivity of data due to differences in individual muscle strength of the study subjects, a normalization stage is necessary with the purpose to evaluate the baseline of the signals. The normalization is performed in 3 phases. First, the subject is required to remain in an idle condition for a period of 5 seconds and during this temporal window the baseline of the sEMG signals for each probe is measured using the mean of the data acquired. Next, the subject executes the ankle plantar flexion against a fixed resistance and holds it constant for 5 seconds to obtain the highest possible sEMG signal resulting from Gastrocnemius Lateralis muscles contraction. The values of Maximum Voluntary isometric Contraction (MVC) [14] are calculated taking the mean amplitude of the highest signal portion of the data acquired. Finally, the subject executes the ankle dorsi flexion against a fixed resistance and holds it constant for 5 seconds to obtain the highest possible sEMG signal resulting from Tibialis Anterior muscles contraction. Even in this case the values of MVC are calculated employing the mean.

B. *Feature extracion*

To evaluate muscle strength, attention was focused on several low computational cost features, commonly used in the analysis of the lower-limb muscle activity. Usually, the analysis of EMG signals can be investigated in two ways based on the time domain and frequency domain characteristics [15].

In the present work, the following low-cost time-domain features were computed and tested for each probe: Root Mean Square (RMS), Simple Squared Integral (SSI), Integrated EMG (IEMG), and Waveform Length (WL). The features were evaluated through the following mathematical equations:

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} EMG_i^2}{N}} \quad (1)$$

$$SSI = \sum_{i=1}^{N} |EMG_i|^2 \quad (2)$$

$$IEMG = \sum_{i=1}^{N} |EMG_i| \quad (3)$$

$$WL = \sum_{i=1}^{N-1} |EMG_{i+1} - EMG_i| \quad (4)$$

The RMS value has been used to quantify the electric signal because it reflects the physiological activity in the motor unit during contraction. SSI expresses the energy of the EMG signal. IEMG is generally used as a pre-activation index for muscle activity. It is the area under the curve of the rectified EMG signal. Finally, WL is the cumulative length of the waveform over the segment. The resultant values of the WL calculation indicate a measure of the waveform amplitude, frequency, and duration [15].

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III. RESULTS

The hw/sw platform described in Section II has been implemented within the SIMMS project (Sarcopenia Integrated Measurement and Management System), whose purpose is to develop an integrated technological system, consisting of measuring devices, including mobile and wearable devices, which interface with a software system for data collection and processing, clinical monitoring, and management of sarcopenia. Due to COVID-19, the trial was started with considerable delay, consequently at the time of writing this document the results obtained on samples of patients monitored directly in hospitals are not yet available.

However, to validate the platform primarily in controlled contexts, experiments were carried out within the laboratory used as a "smart home", located inside the Institute for Microelectronics and Microsystems (IMM) in Lecce. A total of fifteen participants, six young (mean age of 34.8 years), five middle-aged (mean age of 53.1 years) and four older (mean age of 68.7 years) women and men participated in this study after providing voluntary consent. Table 1 presents the total number of participants in the preliminary experimentation, broken down by age group and gender:

TABLE I. TOTAL NUMBER OF SUBJECTS INVOLVED IN THE EXPERIMENTATION BROKEN DOWN BY AGE GROUP AND GENDER

Gender	Age (years)			
	(29-47)	(48-64)	(> 65)	Total (29-73)
Male	4	3	2	9
Female	2	2	2	6
Total	6	5	4	15

The study involved data analysis during the execution of two different tests: 1) the walking test and the 2) sit-to-stand test. The walking test consisted of the subject being monitored in the execution of a 5-meter journey, whereas sit-to-stand (Figure 5) is commonly used in clinical context for evaluating lower limb muscle function [16].

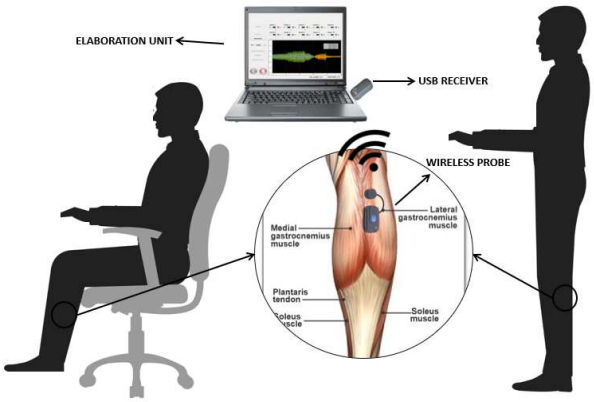

Figure 5. Sit-to-stand test setup.

The objective of the first experiment was to evaluate the mean and variance of the features introduced in the previous section by acquiring the EMG signal with different sample rates. Tables 2 and 3 report the mean and variance of the feature values for each test required by the experimental protocol, and considering 250Hz, 500Hz and 1000Hz as sampling rate of the raw EMG signal.

TABLE II. MEAN AND VARIANCE OF THE FEATURE AT VARYING OF SAMPLE RATE DURING THE EXECUTION OF WALKING TEST

Sampling Rate	Feature			
	RMS	SSI	IEMG	WL
250Hz	0.36 (0.07)	13.01 (3.88)	36.05 (5.23)	.12 (0.06)
500Hz	0.56 (0.04)	31.57 (2.90)	56.18 (2.52)	.26 (0.03)
1000Hz	0.58 (0.03)	35.33 (2.78)	59.43 (2.38)	.28 (0.02)

TABLE III. MEAN AND VARIANCE OF THE FEATURE AT VARYING OF SAMPLE RATE DURING THE EXECUTION OF SIT-TO-STAND TEST

Sampling Rate	Feature			
	RMS	SSI	IEMG	WL
250Hz	0.87 (0.11)	22.09 (5.78)	52.18 (6.55)	.86 (0.10)
500Hz	1.16 (0.07)	43.12 (4.19)	71.34 (4.11)	.33 (0.08)
1000Hz	1.19 (0.05)	49.19 (3.53)	76.21 (3.78)	.47 (0.05)

The two previous tables show how the absolute values of the features have a limited variation when the sample rate is halved from 1000Hz to 500Hz while there is a fairly evident variation when the raw EMG signal is sampled at 250Hz, and this is true for each considered feature and for each of the two tests performed by the subjects involved in the experimentation.

The second experiment aimed to evaluate the time interval required to extract the features with different sample rate and as the duration of the exercise changes. Tab. 4 reports the average processing time of the features extracted during the walking test by varying the duration of this test in the time interval 30 seconds - 2 minutes. This assessment was not necessary for the sit-to-stand test due to its limited time duration.

TABLE IV. PROCESSING TIME (EXPRESSED IN SECONDS) FOR THE FEATURE EXTRACTION AT VARYING OF WALKING TEST DURATION

Sampling Rate	Walking test duration			
	30 sec	60 sec	90 sec	20 sec
250Hz	0.848 s	1.345 s	1.786 s	.124 s
500Hz	1.112 s	1.732 s	2.203 s	.568 s
1000Hz	1.121 s	1.918 s	2.413 s	.834 s

From the analysis of the data reported in the previous table, the variations in computational times are negligible. Consequently, to obtain the best trade-off between accuracy in the evaluation of the features and computational cost, the sample rate was set to 500Hz for the subsequent validation in the clinical context.

A. *Clinical protocol for validation*

Due to the COVID-19 emergency, the initial 6-month test phase was reduced to approximately 2 months and will be performed at Casa Sollievo della Sofferenza Hospital in San Giovanni Rotondo (Lecce, Italy) on a randomized cohort of 100 patients aged ≥ 65 years and at risk or suffering from sarcopenia (i.e., ADL ≥ 4 and SARC-F ≥ 4), either admitted to the Geriatrics Operational Unit or evaluated at the Geriatrics clinic. The study will focus on the assessment of sarcopenia and will be carried out

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according to the EWGSOP2 guidelines [17] in which muscle strength, muscle mass and functional status will be determined. For the evaluation of muscle strength, the EMG platform described in this paper will be used. Moreover, the total body Skeletal Muscle Mass (SMM) and the Appendicular Skeletal muscle Mass (ASM) will be determined during the clinical trial and their values will then be corrected for BMI. All data will be recorded and subsequently entered in a digital platform through a mobile app carried out within the same project by a private partner.

IV. CONCLUSION

The sEMG platform described in this work was developed within a larger research project (SIMMS project) that is referred to the development of an integrated technological system, consisting of measuring devices, including mobile and wearable devices, interfacing with a data collection and processing software system, that can be used for early diagnosis and monitoring of sarcopenic patients.

All the devices included in the technological system can evaluate sarcopenia-related parameters through the use of wearable devices. Specifically, the implemented sEMG platform was designed and developed to provide doctors or caregivers with a decision support tool to evaluate in an innovative way the temporal evolution of sarcopenia. Another added value of the platform is that all collected information can be sent to a software platform through an app developed on smartphones for patients, caregivers or doctors and can be consulted by medical personnel through a web application for diagnosis and interventions.

As future work, regarding the EMG data, correlation will be extrapolated and statistical analyzes will be carried out on time series of the extracted features with the aim to implement an intelligent and automatic tool for early diagnosis of the considered pathology.

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