Data Acquisition System for a Wearable-Based Fall Prevention

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Abstract: Reliable ways to treat and monitor patients remotely have been researched and proposed by numerous people. Many of these propositions are under the wearable category due to it usually not requiring deep knowledge to be handled and its durability. Among the many applicable ways, fall monitoring has gained importance as the world population ages and countries aim to increase the quality of life. For it to be possible, there are many ways such as analyzing muscle response, body position, or brain activities, but for most of them, the result ends up being expensive and or inaccurate. With this in mind, this paper brings the development of an acquisition system for electromyography, electrocardiography, body position and temperature. The acquired data is transmitted to the smartphone through Bluetooth Low Energy (BLE) and then sent to a secure cloud to be provided to the physician. In future works, artificial intelligence codes will analyze the data patterns to predict fall occurrences and establish functional electrical stimulation (FES) routines to prevent falls and or treat the patients according to their necessities.

1 INTRODUCTION

Isolated in their homes, elderly people with mobility issues are mostly unable to receive common treatment from clinics, since constant consultations may become a financial burden, and prolonged consultations are more demanding on therapists and increase patient discomfort. A quick solution to this kind of situation is requiring the health professionals to have a more direct approach and move to each patient's house, however, is fated to become an obstacle to the health system. That is because the number of people requiring treatment increases at a higher rate than the amount of specialized caregivers (WHO, 2022).

It is difficult to hope for the elderly to keep exercise or treatment routines by themselves, which just increases the burden on professionals and relatives. Besides, even with proper treatment, the high amount of time they are left alone in their houses increases the chances of them falling or suffering any injury, and not be found by anyone for a long time. Even when considering home treatment, visits may prove themselves of no help if taken into account that the cause of the problem can be an isolated event, that may not occur or goes unnoticed during the visit (Jeong et al., 2021).

When dealing specifically with the fall problem, it is difficult to consider the early diagnosis as an alternative. This is due to the diverse and complex fall causes, and also individual susceptibility (Rakugi et al., 2022). This problem can be easily overcome by including non-invasive monitoring and rehabilitation devices. These devices can be implemented in wearables and can be used to remove the need for constant human interference.

Up to date, there are wearables with capabilities to analyze muscle, heart, and brain activity, or other data signals such as body temperature and position. It is also possible to monitor other parameters, but these may require invasive sensors which, in addition to be-

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ing uncomfortable, make it difficult for patients without the necessary expertise to use them. Other models present treatment features like electrotimulation to assist physical therapy, an example is Functional ELectric Stimulation (FES), but they usually also require specific knowledge to some degree.

The number of signals that make it possible to access the patient's current situation allows many possible combinations, but implementing all of them together is a problem. Since it would increase both the number of components and the price. That way, this work brings the development and implementation of a modular biosignal acquisition system specially developed to be integrated together with FES actuators. The aim is to analyze the data with AI and generate personalized FES routines for treatment or impulses to prevent muscle imminent failure that would lead to a fall. For it to be possible, the stabilizing muscles located in the abdomen and lumbar are monitored and stimulated individually. So each one of the target muscles require a pair of EMG sensors and a pair of FES actuators.

However, the description and analysis of the stimulation system and the AI structure are outside this paper's scope due to their complexity requiring a more in depth study. Therefore, this work will focus on the acquisition portion of the system, i.e., electromyography (EMG) from the stabilizing muscles located in the abdomen and lumbar, electrocardiography (ECG), body temperature, and position change (IMU). Figure 1 (Muharrem Adak, Vecteezy, 2022) exemplifies the placement of EMG and ECG sensors, keeping in mind that the placement may present slightly variations according to the patients' anatomy. The temperature and IMU sensors present a much more flexible position range, being highly dependant on comfort and practicality.

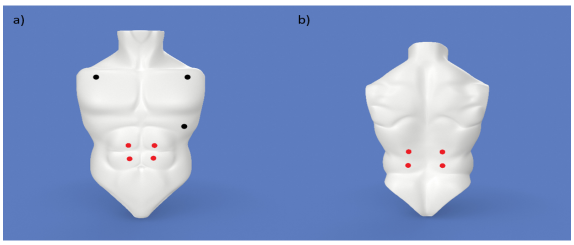

Figure 1: Placement of EMG (red) and ECG (black) sensors from the front (a) and the back (b).

Acquiring EMG signals allow the visualization of the stabilizing muscles' behavior, i.e. when they work properly in a coordinated way to maintain the patient stabilized or when there is some abnormality. The same applies to ECG signals; if the cardiac waves present abnormalities or sudden changes, the patient may have had a problem and needs help. The IMU helps in monitoring the angular displacement of the upper body that, together with the EMG signals, allows the physician team to determine if the change was voluntary or a fall. To complete the acquired data, body temperature will be constantly verified since it often indicates health problems or other factor changes.

The data acquired from both the electrodes and the other sensors (IMU and thermometer) will be wirelessly transmitted to the smartphone with Bluetooth Low Energy (BLE) without being treated to reduce the delay (Qian et al., 2017; Marin-Pardo et al., 2020). The smartphone then serves as a mediator to the cloud where the data stays available to the physician to consult and make decisions and to AI algorithms to analyse the patterns and predict the falls.

The paper is separated as follows: Section 2 presents the related work. Section 3 describes the proposed architecture and system requirements while Section 4 focus on the implementation of the proposed acquisition system and explains the functionalities and integration of the circuit modules. Section 5 analyses the prototype experimental results and Section 6 summarizes the conclusions and points out the future work.

2 RELATED WORK

With higher living standards, well-developed countries tend to research and develop systems to improve the quality of life of the elderly, being fall detection one of the most researched (Wang et al., 2020). The problem is that for most systems, the detection often results in false alarms due to imprecise data input and analysis. Recent studies indicate that fusing the signals of different sensors is ideal to lower the false alarm occurrences of fall detection and prediction system (Siwadamrongpong et al., 2022). Besides the increase in accuracy, analyzing multiple signal responses improves the robustness of such systems, since it needs more indicative responses to trigger the alarm.

Examples of devices with only one type of signal input such as EMG are often found in the literature (Zhu et al., 2021; Ali et al., 2021; Steinberg et al., 2019). Even for the works that develop one device capable of acquiring different signals, the inability to treat and analyze these signals in an integrated way is a problem (Wearable Sensing, 2022). This increase both the cost and the amount of components patients need to deal with to be able to monitor their daily life. Some works reported simpler technologies with higher accuracy such as computer vision and doppler radar (Ren and Peng, 2019) but these tend to be expensive. Regardless of their precision, both these systems and the less accurate ones present the same problem, they only detect the fall after it occurs or during the fall.

Aiming to predict the fall and with improvements in electronics and materials, medical diagnosis devices started to be integrated into wearables without compromising the patient's flexibility, easy mobility, and capacity of executing their daily tasks. These wearables can be found in various forms and shapes, such as watches, t-shirts, armbands, etc. Most devices are projected to monitor vital signals (Lou et al., 2020) and, recently, there is a tendency to invest in wearables with extra functionalities (Bruce-Brand et al., 2012; Qian et al., 2017) like life support systems.

There are many different ways to detect a fall with sensors adaptable to wearables, such as analyzing the muscle response through EMG signals. (Biometrics Ltd, 2021) is one of the many sellers of EMG sensors and systems ready to be used for research and other purposes. But, as said before, to increase the precision of the systems, fusing other signal responses with EMG is necessary.

Combining EMG and IMU responses, (ZiYing et al., 2021) uses machine learning techniques to treat the data and, based on previously known patterns, decide if the current combination of inclination and muscle response is leading toward a fall. All this data is sent via Bluetooth to a computer, which decreases the practicality of the device by having to stay near a computer during the monitoring. Other works also see the importance of implementing some type of artificial intelligence (especially machine learning) to better perceive the EMG patterns and risks of falling (Jeong et al., 2021; Rescio et al., 2018).

A different approach is shown by (ZiYing et al., 2021) where the system's main routine is to detect Movement Related Cortical Potential (MRCP) through an electroencephalogram (ECG). When there is an intention of movement, the EMG sensors are activated and the force threshold is verified to decide if there is enough force to realize the movement. If the threshold is below the necessary, the patient is instructed to wait for aid and the caregiver receives a warning about the situation.

Just like EMG, there is still the application of ECG as the main parameter for fall risk assessment (Shimmer Discovery in Motion, 2022). Since the ECG acquires the response from the heart, analyzing anomalies in the cardiac waves may reveal a possible fall event. The number of works using mainly ECG or a fusion of cardiac signals and some other parameter increases each year but the tendency is for them to integrate some type of artificial intelligence into it (Butt et al., 2021; Melillo et al., 2015). This integration of ECG and AI tends to show good results when predicting fall risk and lessens the burden on specialists (Queralta et al., 2019).

3 SYSTEM DEVELOPMENT

By combining the responses from diverse biosensors, this work's aim is to analyze a modular system to acquire, process and transmit the necessary biosignals. These signals include the EMG signal of the abdomen and lower back, ECG, IMU (by verifying if the subject is inclined or upright) and body temperature. Later, these signals are to be used as input for AI codes to create personalized FES routines.

3.1 System Requirements

Each biosignal that must be acquired has different properties and so, presents different system parameters requirements, all of which must be handled by the same microcontroller. Starting with EMG acquisition, to properly acquire the muscles' responses the sampling rate of the acquisition must be at least 1 kHz on a frequency bandwidth of $18-480$ Hz. To acquire the response of four pairs of electrodes (two pairs at the abdomen and two at the lower back), the microcontroller was configured to receive data through multichannel.

Regarding the ECG signal acquisition, the frequency bandwidth can vary from 0.5 Hz up to 200 Hz and the best sampling rate frequencies are around 120 Hz and 200 Hz (Kwon et al., 2018; Ajdaraga and Gusev, 2017). The system also must include basic signal treatment features to eliminate power line noise which alters the ECG signal acquired around the 60 Hz.

Unlike the previous two signals which were signals acquired directly from the body, the response of the IMU comes from an accelerometer and a gyroscope, each generating three responses, one for each axis (x, y and z). These two devices work with a different communication protocol called Inter-Integrated Circuit, or I2C what prevent the IMU acquisition rate to be managed by the ESP-32's timer, and instead, works based on code routines. With this, the sampling rate was set to 100 Hz (Zhou et al., 2020) since it is the minimum necessary to accompany simple daily movements

The developed system also must be prepared to handle a body temperature sensor. This sensor will acquired the body's temperature with a sampling rate of 10 Hz in the same way the IMU, following the code routine.

Since the purpose of this work is to develop the necessary microelectronic to acquire and transmit biosignals from inside a wearable, there are a few requirements it must follow besides the ones specific to each signal and circuit. To not influence the daily activities of the patient, the final circuit must be light and small without compromising comfort when wearing the T-shirt.

Another factor to be taken into account when thinking about not interfering in the daily tasks is the absence of wires, i.e., the circuit must be wireless both for energy source and data transmission. To avoid battery discharge in the middle of the session, energy-efficient batteries and a battery monitor are also requisites included in the scope of the project.

Fulfilling all these requirements while using high-end materials with their durability and quality would be an easier task, but the cost would turn exponentially higher. To ensure that most people have the possibility of owning one exemplar, the cost of the final product must be kept accessible while using durable and trustworthy materials.

3.2 System Architecture

The proposed architecture, illustrated in Figure 2, constitutes an advanced technological system/medical device with biofeedback response, since the built-in sensors/actuators will be able to monitor muscle and vital signs and, at the same time, act by functional electrical stimulation (FES). Furthermore, the device allows to work as an emergency system, in situations of imminent fall, in which the sensors will trigger a muscle activation, remotely controlled, of the abdomen and/or low back muscles.

The designed system offers the possibility for the patient to carry out the therapy comfortably at home, allowing the reduction of social and economic burdens, as well as the opportunity for hospital centers to reduce the number of falls of users in the context of hospitalization. The proposed wearable device is responsible for ensuring the acquisition and conditioning (amplification, filtering and conversion) of the EMG, ECG, IMU and temperature data properly, and subsequently send the acquired information to a mobile application running on a smartphone/tablet.

The EMG sensors are destined to capture the musculoskeletal signal, which measures the potential difference between the muscle fibers recruited during a muscle contraction. In this way, the designed architecture employs four pairs of EMG sensors, two for the abdomen and two for low back muscles to monitor the signals aiming to assist the fall detection system.

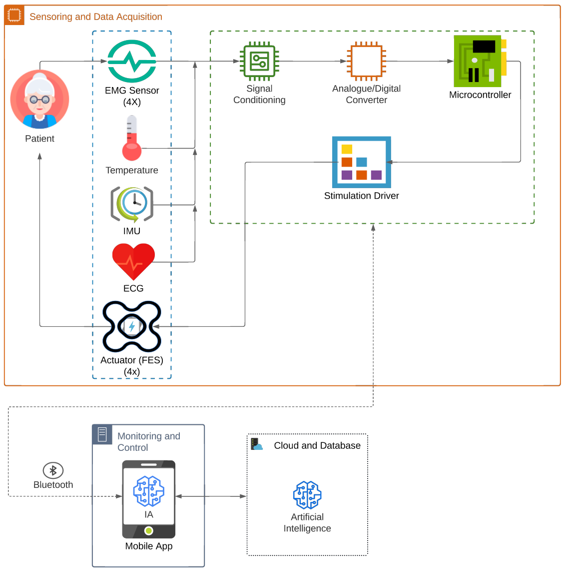

Figure 2: System architecture focusing the acquisition, signal conditioning and stimulation system.

The ECG electrodes allow monitoring of the user's heart rate, which can be useful to check if a fall has occurred or even alarm if another heart disease is detected. This allows us to understand the level of physiological arousal that someone is experiencing, but it can also indicate a better understanding of the psychological state (Berkaya et al., 2018). Therefore, recording heart rate data gives access to several parameters, such as Heart Rate (HR) that reflects arousal, Inter-Beat Interval (IBI) and Heart Rate Variability (HRV), that are closely related to emotional arousal (Berkaya et al., 2018).

Temperature sensor affords to measure the patient's body temperature, which allows to monitor and alarm if any anomaly occurs. The sensor is positioned in the core, that refers to the temperature of the body's organs. This metric fluctuates following physiological processes, such as circadian cycles, menstruation, illness or physical activity (Mina, 2021). Regarding remote patient monitoring, variations in core body temperature often provide insight on health-related problems prior to the appearance of other symptoms (Dolson et al., 2022). Therefore, accurately monitoring the patient's body temperature can help to identify issues at an early stage.

The IMU provides to measure the acceleration and angle, which allows jointly with the EMG to perform the biofeedback for the stimulation module in the fall detection system. Therefore, IMU sensor is the most significant in the wearable its metrics will be the base for the fall detection system where according to the patient's core angle and the acceleration value, then the respective actuator array will be powered on in order to compensate this undesirable motion and re-establishing the patient corporal posture.

The FES actuators perform the electrostimulation through electric pulses, aiming to assist in the user posture correction and preventing imminent falls registered by the monitoring system. These actuators are crucial in physiotherapy and monitoring contexts aiming to strengthen the muscles of the abdomen and low back, that are the main muscular group recruited for posture stabilization and elderly people usually have atrophy in these muscles, which contributes to an increased risk of falls.

After collected each information from their respective transducer, it is forwarded to a signal conditioning block that provides a properly amplification to a higher amplitude aiming to decrease the transmission losses, in addition, this same block allows to filter the signal to attenuate undesired frequencies and noise.

Next, all the sensor data is converted from analogue to digital through an Analog/Digital Converter (ADC) to be able to transmit all content to the microcontroller unit (MCU). The MCU will receive all the information, store it and process locally the data by executing control rules to perform the muscle stimulation function. These control rules triggered according to the biofeedback from the EMG and IMU collected data (providing a loop between the acquisition and stimulation systems). Therefore, the MCU will send commands to the stimulation driver according to the IMU angle and acceleration values, to avoid imminent falls and guaranteeing the user integrity and health.

The mobile application is responsible for managing the information that defines the treatment sessions in real-time, that is, receiving the data collected by the set of sensors and sending the stimulation rules considering the biofeedback to the wearable system. This management is done in the mobile app due to its greater computational power, enabling more complex algorithms to be explored to provide adequate stimulation adaptation for each patient.

In this way, before a treatment session starts, the initial configuration parameters defined by the physician are downloaded from the cloud to the mobile app. During the session, the mobile app will only communicate with the wearable, requiring no internet connection to perform the session. When the session ends, all the data collected and the stimulation rules applied will be sent to the cloud and be available for the physician to evaluate and prepare the next treatment session.

4 SYSTEM HARDWARE DEVELOPMENT

Considering the aforementioned project requirements and the designed system architecture, a prototype of an integrated acquisition system was developed as illustrated in Figure 3 (note that the stimulation system, the mobile app, the fall detection system and the AI algorithms are not detailed in this paper). The proposed solution comprises the data acquisition of EMG, ECG, IMU and temperature, which operates in real-time and integrated with the mobile app.

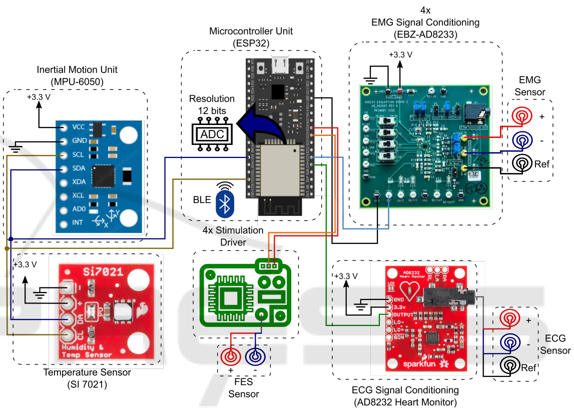

Figure 3: Schematic of prototype data acquisition and stimulation.

4.1 Bio-Signal Acquisition Module

The designed acquisition prototype employs commercial and low-cost sensors, namely MPU 6050, EBZ-AD8233, SI 7021 and AD8232 Heart Monitor, as presented in Figure 3.

Seeking to measure the signals produced by the abdomen and low back muscles, the evaluation board AD8233 was selected to perform the signal conditioning (amplifying and filtering). Originally, this device was designed by the Analog Devices, Inc. (ADI) as a heart rate monitor front end to acquire ECG signals providing a frequency bandwidth of $7-25$ Hz. Then, aiming to measure EMG signals an adaptation in the components of the High-pass (HPF) and Low-pass (LPF) filters circuits were necessary, resulting on a new frequency bandwidth of $15-480$ Hz. Those changes allow to acquire and amplify musculoskeletal signals properly since the biosignals have low amplitude levels, ranging from µV to a few mV.

The AD8232 Heart Monitor is a low-cost development kit specified for ECG signals, which offers complete voltage interval for reading $(0-3.3\ \mathrm{V})$ to sample the heart rate signal amplitude and provides a frequency spectrum of $7-500$ Hz. ECGs can be extremely noisy, the AD8232 acts as an operational amplifier (op amp) to assist obtain a clear signal from the PR and QT intervals easily. Furthermore, this integrated signal conditioning block is designed to filter small biopotential signals in the presence of noisy conditions, such as those created by motion or remote electrode placement.

The temperature sensor SI 7021 offers a 400 kHz I^2C bus communication, high accuracy for a low-cost device $\pm$ 0.4 °C providing a temperature ranging of -10 °C to 85 °C, and low-power sensor presenting 150 µA of active current.

The IMU sensor adopted is the MPU 6050, which offers a 400 kHz I^2C bus communication, a low-cost sensor, low power consumption 3.6 mA and 500 µA operating currents of the gyroscope and accelerometer respectively, and high-performance requirements for wearable devices. This sensor model allows tracking 6-axis motion, being 3-axis for the gyroscope and 3-axis the accelerometer. Moreover, the MPU 6050 enables to follow fast and slow motions providing a user-programmable scale for the gyroscope $(\pm 250, \pm 500, \pm 1000, \pm 2000)$ °/s and accelerometer$(\pm 2g, \pm 4g, \pm 8g, \pm 16g)$ m/s^2.

4.2 Microcontroller Unit

To be possible to read data from all the sensors, a MCU was employed to lead all acquisition and transmission functionalities, as presented in Figure 3. Therefore, the whole system architecture was based on the ESP32 microcontroller which offers low-cost, wireless communication (Wi-Fi and BLE) and capability to operate with dual core.

ESP32 is a MCU with enough computational power to acquire sensor data from all the sensors, being capable to operate at high frequencies since the clock of a standard model, such as *ESP32-WROOM-32D*, is above 150 MHz. In addition, the ESP32 allows separating through timer tasks the distinct acquisition routines for each sensor, respecting their sampling frequencies while avoiding delays and data losses.

The ESP32 has an ADC with 12 bits of resolution, permitting to convert analogue voltage values from 0.8 mV while e.g. the Arduino microcontroller only has 10 bits of resolution that allows to measure a signal from 4.89 mV. Lastly, this device provides a dual-core functionality that is essential to guarantee the correct acquisition and data transmission integrated, being able to execute separately each function without delays or interference among the tasks.

4.3 Data Transmission

The data transmission between the microcontroller and the smartphone was an important part of the project having in mind that data loss during the communication could lead to wrong or incomplete information being displayed to the medical team. Aiming to implement a reliable transmission technology with enough security and customizable, Bluetooth Low Energy (BLE) was implemented.

Besides the items aforementioned, BLE is supported by most smartphones, tablets and similar devices nowadays. The coverage range of BLE 4.2 also reaches greater distances, even being able to communicate at around 100 meters. Power consumption that is already low for this version can be lowered even more with simple configurations, what is an advantageous point for a wireless wearable powered by batteries.

Serving as the central, the mobile application is responsible for sending requests to peripheral device (the wearable) to read and send the acquired data or to write new routines. In the meantime, the peripheral device can only send indications, responses to requests and notification about characteristics previously selected during the configuration. Since the ESP-32 employed has to deal with vast amounts of data being transferred regarding all the signals acquired, the signals responses pass through different buffers while the responses required by the client are sent directly. To better handle this task one of ESP-32's threads is exclusively to acquire, manage and transmit the data to the smartphone in real-time.

Expanding the maximum throughput to 517 bytes was another method for improving the transmission performance since with this the computational cost associated to constantly sending and receiving the overhead of packages is lowered.

This necessity becomes even more visible supposing the mobile application will present some type of play/pause/stop command. With this in mind, the transmission code was developed in a way that even if the transmission is paused, biosignals acquisition keeps running on the background while being stored locally to avoid data loss until the treatment is resumed.

5 EXPERIMENTAL RESULTS

In order to verify the accomplishment of the requirements, the prototype was used to perform several experimental tests. The acquired signals were derived from a healthy person executing a simple set of movements during the tests routine. While standing, bend the upper body forward, backward, to the left and finally to the right holding the position for a couple seconds in each one. Afterwards, the subject would strongly contract the biceps once followed by three weaker contractions.

5.1 Data Acquisition Test

Auto-adhesive wet Ag-AgCl electrodes were chosen to ensure that the noise from the sensor/skin interface was the minimum possible. Besides being the golden standard, these sensors present common connection characteristics that allow them to be used with other acquisition devices which makes possible to compare the signals acquired by commercial devices and the prototype.

Although the acquisition boards used are commercially available and already validated, the EMG acquisition boards had some components changed. The resulting acquisition system was then compared with Bitalino's output as can be seen in Figurereffig:comp.

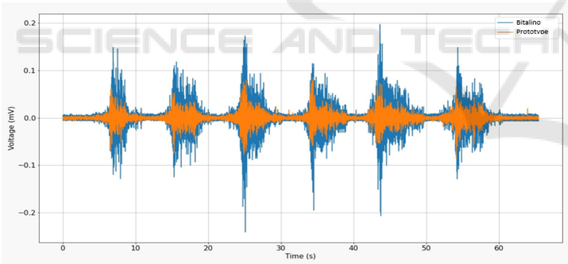

Figure 4: EMG comparison between Bitalino and the prototype.

During the tests, it was verified that simply moving the cables resulted in high noise inputs, sometimes requiring the test to be remade. Even so, the best signal-to-noise ratio when using the prototype to acquire EMG signals achieved 14.68 dB in contrast with 18.15 dB obtained when using commercial acquisition devices.

Figure 5 and Figure 6 are examples of data acquired with the proposed systems.

As can be seen, both signals still have a great amount of noise present, even so, both the biceps contractions and the PQRST complex are clearly detectable. Since the IMU sensor does not need to stay in contact with the body, it can be kept closer to the microcontroller, requiring shorter cables and reducing the movement and instability artifacts. This can be seem in Figures 7 and 8.

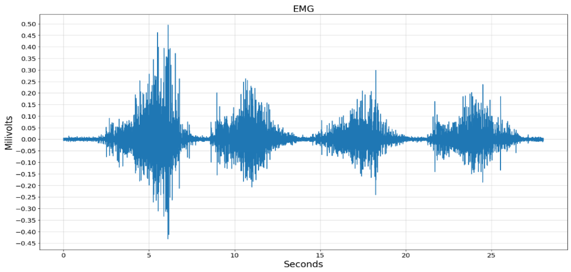

Figure 5: EMG acquired using the prototype.

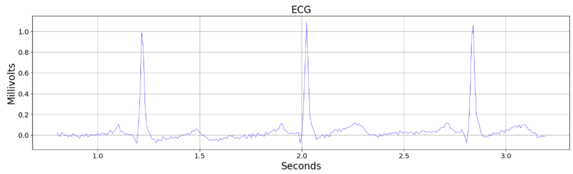

Figure 6: ECG acquired using the prototype prototype.

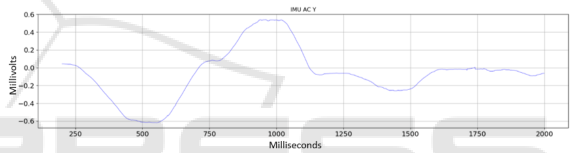

Figure 7: IMU response to bending the body to the front and the back.

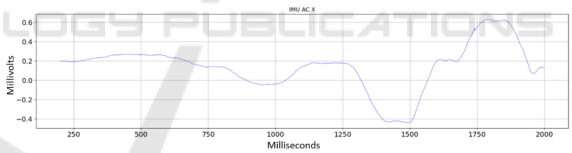

Figure 8: IMU response to bending the body to the left and the right.

Both the EMG and ECG signal, as well as the six IMU responses and the temperature were acquired and transmitted to the microcontroller via cables. For the duration of the tests (approximately one hour and a half), the ESP was able to handle all data without problems.

5.2 Data Transmission Test

Besides acquiring the signals and handling the routines, the microcontroller was responsible for transmitting the data through BLE. This type of communication presents the risk of losing some data be it due to some glitch at the smartphone or the ESP not being able to keep track of the packets sent resulting in packets being skipped.

To closely verify how many packets of each type

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of data was received, the prototype was put to work with simulated values as acquisition's responses. The time between the received packets was monitored for fifty packets for each of the four types of signals. This being said, it is important to note that comparison between two types of signals may cause wrong conclusions as the transmission system works based on buffers, so signals with greater acquisition rates, like EMG, will present smaller time differences than signals with smaller acquisition rates (i.e. temperature).

Figure 9 shows the time between consecutive packets for the acquired data. The ideal response would be to present the same delay between all the packets of one type of signal. To illustrate, if all the EMG packets presented zero and 100 ms consecutively between two packets, it would be proved that, for this signal, the routine is being well handled by the ESP. But as can be seem, the microcontroller presents some problems to handle the acquisition and transmission at the same time around the thirtieth packet which cause irregularities in all four signals transmission.

Even with some irregularities in the transmission, at long term tests the mean time is kept close to the settings so there is no major prejudice to the final data set. Since the ESP has two cores and just one of them is being used to this task, employing other microcontroller with more cores or with higher performance is bound to solve the discrepancies in delay between packets.

6 CONCLUSIONS

Employing wearable systems in daily life is a reliable way to improve healthcare while maintaining the burden on the healing system at acceptable levels. The possibility of remote monitoring of vital signals is an important factor for both health professionals and concerned relatives.

The proposed innovative system aims at revolutionizing the method for detecting fall occurrences with a low-cost modular device embedded into a wearable T-shirt. Acquiring a set of important signals such as EMG, ECG, body temperature and body position allows the usage of this data for not only detecting and preventing falls but to detect improvements resulting from treatments. To provide the acquired data to the medical team this system presents connection to the smartphone, which safely sends the data to the cloud. To lower the burden on the ESP, data treatment and storage are done on the smartphone, which reduces the need for more expensive microcontrollers.

Preliminary experimental tests show that the main acquisition system requirements were fulfilled, mainly regarding the acquisition rates and identification of each signal in the buffers. The microcontroller also proved itself capable of handling the data transmission while keeping the acquisition routines on. There is a need to improve the transmission routines since some packets presented higher delay, although the frequency with which this occurred and the magnitude of the delay did not have great influence in long term.

During the experiments, it was clear that the connections between the boards created instability among the components resulting in motion artifacts and noise increase. Also, isolating one core of the ESP reduced the processing capabilities so using both cores to acquire and transmit the data may present a great positive impact on the result. Implementing the routines in other microcontroller models may be an option as well.

Since the acquisition system was developed to be integrated with the stimulation system, future works are summarized in implementing the necessary electronics and verifying if the microcontroller is able to handle all tasks, taking into account the complexity of the stimulation routines. With both stimulation and acquisition working together, a new printed circuit board (PCB) will be designed to reduce even more connection problems and circuit size. With this, the analysis of the system's integration viability into wearables and battery consumption can be easily and properly done.

Then, the PCB will be used for tests with volunteers for validation purposes and the acquired signals, used to populate the database. With this data, the AI will be trained to develop customized stimulation routines for each muscle according to the necessary treatment or to prevent some fall occurrence.

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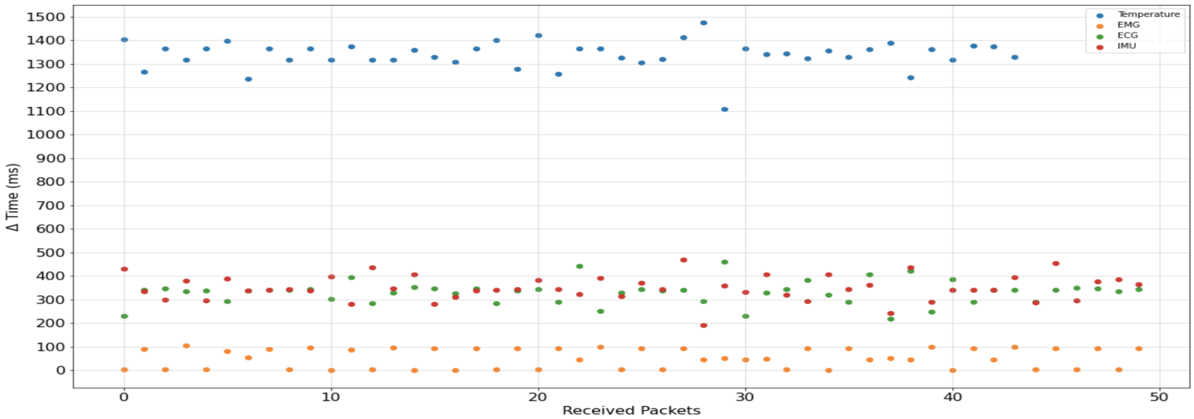

Figure 9: Received Data Packets Δ Time.

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