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Construction of a biosignal measurement device and its dashboard for swimming training

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Preface

This document addresses the use of technological equipment to measure biosignal features in the aquatic swimming environment. The design of a control panel is another core purpose of this work and will provide a way to visualize the monitoring of collected data. As swimming is a dear and familiar subject to the author, this endeavour represents an even greater opportunity.

Covilhã, February 2021.

Resumo alargado

O âmbito deste trabalho incide no desenvolvimento/criação de um dispositivo de medição de biosinais (acelerometria, eletromiografia e eletrocardiografia) para que através de uma conexão via Bluetooth seja feita a captura destes valores num nadador. Abrange ainda o desenvolvimento de um *dashboard* que permite ao treinador acompanhar e melhorar os treinos de um atleta.

Abstract

This research work draws on previous experimental research and aims to further develop and refine a biosignal measurement device that will allow the capture of a swimmer's biosignals via Bluetooth. It also encompasses the construction of a dashboard that will allow a swimming instructor or coach to monitor and improve the athletes' swimming practice.

Keywords

Swimming, Monitoring, Training, ACC, EMG, ECG, Dashboard

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Acronyms List

ACC	Accelerometer
ALLab	Assisted Living Computing and Telecommunications Laboratory
API	Application Programming Interface
BPM	Beats Per Minute
BT	Bluetooth
COM	Communication
ECG	Electrocardiography
EMG	Electromyography
GUI	Graphical User Interface
LiPo	Lithium polymer
MCU	Microcontroller
MEMS	Micro-electromechanical systems
MS	Millisecond
PMC	Percentage Maximum Contraction
PWR	Power
RF	Radio Frequency
RMS	Muscle Fibre Recruitment
UART	Universal asynchronous receiver/transmitter
UBI	Universidade da Beira Interior

Chapter 1

Introduction

This report chapter intends to cover some knowledge of the subject-matter, the purpose of this thesis, goals to accomplish, and lastly, the report structure.

1.1 Contextualization

This work was carried out within the scope of the curricular unit. The dissertation report in Computer Science focuses on the area of sports, specifically on swimming, and includes assisted living computing. The monitoring of the biosignals of athletes performing in an aquatic environment is an issue that is still quite underdeveloped at the national level and confined to the elite at the international level. That way, this project can represent a practical and direct support to swimming performance, providing a better physical monitoring of the athlete and the possibility to further improve the training and recovery methods.

1.2 Problem Statement

The issue is addressed considering two different perspectives. First and foremost, this kind of supporting measurement devices in this particular environment is only available to a few elite swimmers from certain developed nations. This situation is clearly explained by all the institutional financial aids received by those athletes and teams. This conclusion also serves to show that this kind of gadgets can be quite expensive. Furthermore, although all the reasoned research studies conducted have proven the wide range of benefits of using this technology, many coaches are not yet convinced of these benefits or are not even aware of the existence of such technology. Uncertainty and disbelief together with under-financed swimming are seemingly the most important barrier to the use of innovative technology in this sport.

1.3 Motivation

The relevance of this work is amplified by two major distinct incentives. The first and the most important is the strong need for a portable comfortable waterproof measuring device to be used in association with a simple and user-friendly data visualization dashboard. This equipment should be affordable, and every swimming team should be provided with one so that athletes and coaches are capable of enhancing their performance and knowledge. The second motive arises from the experience and love that the author of this thesis has for swimming and for the competition.

1.4 Objectives

This dissertation presents a set of different objectives that can be categorized as being related to hardware or software.
Hardware:

- Development of a biosignals measurement device;
    1. Simple to use and apply with no or little discomfort or inconvenience;
    2. Water proof feature;

Software:

- Development of a real-time data visualization dashboard;
    1. Real-time charts with ECG, EMG and ACC data;
    2. Processed and forged biosignals info;
        (a) EMG signal amplitude;
        (b) Maximum contraction percentage;
        (c) Instantaneous velocity;
        (d) Average/mean velocity;
        (e) Maximum velocity percentage;

1.5 Dissertation Outline

1. **Introduction**

   This first chapter focuses on the framework and contextualization, the problem studied, the motivation and motive, the objectives to achieve, and on the dissertation outline.

2. **State of the art**

   This second chapter presents a thorough analysis and understanding of previous possible complementary works. It also explains which existing solution or software and hardware suggestions work best when dealing any similar problems. It also provides some base and support knowledge about the topic under study.

3. **Hardware development**

   This third chapter covers mainly the implementation and preparation of the hardware equipment. Sections include a brief overview of the equipment information and of device-related as a hole features like cost, architecture, building, weight.

4. **Software Development**

   In this chapter relating the software portion of this work, all the implementations regarding the dashboard are approached. Technologies that allowed this project to be made, the platform used to visualize the data, the models and algorithms utilized in processing, and lastly the results and end-user experience.

5. **Conclusion**

   In this last chapter, the main findings of this work, the goals reached, the prototypes that were developed, and the follow-up work are concisely depicted.

Chapter 2

State of the Art

This chapter includes a comprehensive study of the current work and research studies conducted on the field under study. Different paths were taken to create solutions to similar problems that tend to occur at this stage. Some general knowledge deemed essential to a more thorough understanding of the methods and definitions used in this dissertation are also forwarded.

2.1 Introduction

In the initial segment of this report, several different approaches are made vis-a-vis the correlation, benefits, and difficulties concerning the wearable sensors in swimming practice, as well as the dashboard allowing monitoring and data visualization.

The monitoring and investigation of swimmers and swimming performance using wearable sensors have been the subject of ongoing research for the past thirty years. Since the beginning of the century, progressive technological and equipment wise initiatives have been developed to help and contribute to a high-performance swimming and swimmers. Single sensor platforms have appeared and become valuable strategies for measuring the swimmer execution and performance [DAJ11b].

Coaches in elite swimming carefully plan their athletes' training programmes and require strict adherence of their athletes to those programmes. Nowadays, coaches often use stopwatches to make sure that their swimmers comply with the training programme. In any case, this sort of estimation clearly limits the observation of conceivable outcomes and is subject to human mistakes [SGT17]. When deeply accurate and reliable estimations are required, coaches regularly use 50 Hz standard frame rate video. Nonetheless, while video analysis is exceptionally valuable for accurate estimations and observational learning, it is too time-consuming for the monitoring of daily training practice since the water environment causes impressive challenges for the analysis of video footage [SGT17].

Swimming assessment is generally a labour-intensive process where stroke rate, lap times, stroke phase, and stroke counts are usually manually recorded or extracted from video type data, which is a tiresome and time-consuming process [DAJ11b]. This manual procedure is dependent on high staffing levels and is usually unavailable for routine training exercises or remote zones. Beyond the essential measures above the coordination of key body segments in swimming is of growing interest for swimmers and coaches although it is hard to obtain [DAJ11b]. Athlete and clinical testing for effectiveness examination and improvement are normally performed in the research facility where the desired instrument is accessible and natural conditions can be easily controlled. So, in this environment, physiological characteristics of athletes such as strength, coordination, and aerobic capacity can be assessed. Generally, laboratory studies have limitations. First, they do not replicate the regular training nor competitive environment. This is even more accurate for the aquatic environment. Furthermore, laboratory-based assessment is generally based on physiology and less suited for biomechanical measures. For the sport of swimming, the in-pool monitoring is, for the most part, available merely at high-performance facilities and usually includes video analysis and a few automated timing strategies. Together with hand counted information, post session examination of video is used to develop comprehensive performance measures [DAJ11b].

Frequently used assessment methods can be separated into three broad areas, although there is significant overlap between them.

- Performance monitoring contains quantifiable and measurable movements of the swimmer during the observation/monitoring period and is regularly related to their development such as splits and lap times [DAJ11b].
- Biomechanical monitoring, a complex part of performance analysis, adopts direct and indirect measurement strategies to quantify the exercise operation of the swimmer, usually to map them to theoretical and logical models and standards [DAJ11b].
- Physiological examinations mainly deal with the energy systems of the athlete during practice, competition, and recuperation/recovery [DAJ11b].

Recent research conducted in the field has recognized modern measures such as the coordination of key body. These new measures are challenging to obtain using conventional methods. Understanding these actions can help understand whether the activity is improving swimming performance or is potentially harmful [DAJ11b]. The enhancement of efficiency in sports is strongly related to training strategy combined with the wellbeing, fitness, and health status of the athlete. Coaches make a consistent endeavour to alter the motions and training cadence of the athletes, particularly in rhythmical and cyclic sports such as swimming [M.S11].The development of a total wearable swimming framework for performance analysis, along with a model application and of course from a systems angle, checking body segment motions, and calculations to enable the detection of swim stroke attributes and consecutive helpful assessment by the athlete and training staff people is of the utmost interest [DAJ11a].

In [SLA10], an assessment of current methods of swimming investigation identified a capability gap in real-time quantitative input. Several components were created to produce a unified system for comprehensive swim efficiency and performance assessment in all phases of the activity, starts, turns, as well as free swimming

- the measurement prerequisites, i.e., what does the end user want to measure;

- the process prerequisites, i.e., how would these measurements be accomplished;

The components created in this research worked towards modern technologies to foster a wider range of quantifiable features using automated models as well as the application of different forms of technology to support the automation of these ongoing procedures [SLA10].

Scientists and engineers from different colleges and companies have proposed several observations and monitoring solutions, techniques, and mechanisms for a wide range of possible goals, from technical applications to leisure. The development as well as the assessment of general monitoring solutions for physiological and biomechanical signals from a swimmer under ordinary training conditions, both in and out of the water, has provided promising information and contributed to design alterations [ASSC11]. Apart from vital signs, other physiological and/or biomechanical signals can be crucial for improving an athlete's efficiency and reducing fatigue when subjected to different types of practice or competition challenges [ASSC11]. In [SLA10], each technology component was not used in isolation but was supported by other synchronous data acquisition. In all instances, a vision component was used to enhance comprehension of data outputs and provide a medium that coaches and swimmers were comfortable with interpreting. The capacity to create valuable, quantitative feedback data for swimmers is always a priority. The turning phase was also portrayed in acceleration space, allowing the phases of the turn to be separately assessed and their contribution to the total turn time established [SLA10].

The improvement of wearable monitoring equipment for sports practitioners, both amateurs and professionals, can present a few perceptible repercussions in the sports community, both regarding the optimization of the training procedures of elite athletes, as well as to the promotion of security protocols in rehabilitation and leisure ventures [ASSC11]. Electromyography, cardiac rhythm, respiratory effort, oxygen consuming taxes, motion capture, wrist and arm increasing speed and rotations, speed, hydrodynamics' pressure; constitute a few of the useful parameters to be collected using a complete wearable system. These can be used for a wide range of calculations, models, and applications of varying nature [ASSC11]. The improvement of electromyographic equipment for the capture of electric outputs produced in voluntary complex motions and the improvement of methodological methods to data collection and computerized analysis of patterns explain the increased applications of EMG in bioengineering, rehabilitation, sport, and in related biomechanics, physiology, and zoology and to a lesser degree in ergonomics [JPCH88].

As for other type of sensors, new improvements in water-resistant, commercially available tri-axial accelerometers provide openings for continuous monitoring of numerous swimmers with significant safety and authenticity. Different research studies have analysed the use of accelerometers for the measurement of lap time, stroke count, and stroke rate for the different stroke types [SGT17]. Tri-axial accelerometers can be used to accurately, faithfully, and reliably measure swimming parameters and monitor practice execution and effectiveness [SGT17]. Tri-axial accelerometers may therefore be used to analyse the adherence of each swimmer to preset training objectives. Additionally, they provide the coaches with increasingly meticulous data to guide and monitor specific training practices. When real-time collection and transmission of the significant data becomes reality, coaches will no longer need to use a stopwatch to monitor the practice of multiple swimmers [SGT17]. Consequently, they will have more spare time to provide swimmers with feedback on technique or motivation, for instance. Nonstop monitoring of the training process with tri-axial accelerometers may allow extra data on dose-response relationships and the balance between load and load capacity. The use of tri-axial accelerometers is a capable instrument for coaches to optimize the training practice and long-term training options [SGT17].

In [ASSC11], the answers provided were, for the most part, restricted to a controlled laboratory environment, and used unpleasant tools and methods for fixing sensors to their planned location. Even though the therapeutic, medical, and sports community have benefitted and improved from such information collection methods for decades, more extensive approaches are currently available. Besides, the need for a more controlled environment and particular laboratory setups increased the related research costs and limited the amount of time spent with the athlete, rarely achieving to gather the information that truly reflected the normal behaviour or efficiency of the individual in natural conditions [ASSC11]. Interestingly enough in [M.S11] the results and outcomes can be effortlessly applied to other sports and areas, such as wellbeing monitoring in leisure sports, and for the elderly patients suffering from a heart condition [M.S11].

Even though swimming has the dominant component of movement in one direction, data contained in the other axes of motion is crucial in identifying stroke traits, performance, and accuracy. Using wearable sensors and specifically resistance sensitive ones is an emerging area in sports monitoring and a promising instrument for swimming assessment [DAJ11b].[SGT17] demonstrated that lap times determined from accelerometers were significantly more accurate than manually collected information. Several researchers have proven the legitimacy and reliability of stroke rate and stroke count using either zero-crossing or peak detection algorithms. Additionally, Magalhaes in [SGT17] showed that accelerometers provide a solid way to assess the biomechanics of swimming performance. Accelerometers are found to allow for continuous monitoring and for identifying fluctuations in swimming techniques caused by fatigue on the basis of accelerometer output signals.

To sum up, accelerometer sensors represent a promising device for continuous monitoring of different athletes, swimmers more precisely, during practice, but unfortunately, data of their use during routine training practices of elite swimmers is scarce. Although there is evidence of great authenticity, reliability and validity, the empirical rules of conduct used thus far were generally brief and did not cover whole training sessions. In addition to reliability, these triaxial sensors can be used to measure different parameters at the same time allowing coaches to gather additional valuable data from the assessments. It is especially interesting to confirm if swimmers fulfil the training goals the way they were defined by their coach, making performance and agreement between the coaches' expectations and the athletes' functions and times much easier [SGT17].

2.2 Biosignal measurement devices in swimming

One side of this double-sided coin is the part that covers the development of a measurement device that can fully respond to the needs is it meant to answer. In the scientific community, and as far as swimming is concerned, there are a reasonable number of intricate mechanisms that serve this purpose, although a significant part of said tools is narrowed to a specific elite swimmers, teams, and nations. This type of equipment usually comprises many sensors. The most commonly used are gyroscopes, accelerometers (ACC), eletromyography (EMG), eletrocardiography (ECG).
There have been many approaches and methods on a multitude of experimental measurement devices. Some of its attributes worth mentioning.

- According to [DAJ11a] the use and application of accelerometers to measure activity levels for sporting (Hawley, 1999; Montoye et al., 1983) health and for gait analysis (Moe Nilssen Helbostad, 2004) is emerging as a popular method of biomechanical quantification of health and sporting activity
  - The swimming nodes should be small in size and designed to be worn on body segments of interest, typically lower leg, lower arm, and the sacral or cervical regions. The device is controlled using a microcontroller with a scheduler based operating system to conserve power and is custom packaged with a user interface and USB port that is fully waterproof [DAJ11a].
  - This study describes the comparable and at times improved convenience and accuracy of the sensors over video for timing and body orientation. Results and derivative data from these swimming technologies, including stroke characteristics for a variety of training strokes have been found to be better than hand timed data and video analysis (Davey, Anderson, James, 2008) [DAJ11a].
  - The real time communications of sensor data in the aquatic environment has been considered difficult, as the transmission range in water is just a few centimetres, with ordinary antenna at popular frequencies (James, Galehar, Thiel, 2010) [DAJ11a].
  - A 2.4GHz transceiver (nRF24L01+) provides wireless communications between multiple sensor nodes and master using a custom protocol. The wireless communications allows the machine to control a number of sensors; including wireless data download and synchronization of events. This system is intended to operate at short distance [DAJ11a].

    The device in 2.1 is equipped with a low-power 8-Bit Atmel microcontroller. Using a high-performance architecture and a USB 2.0 controller data trans-

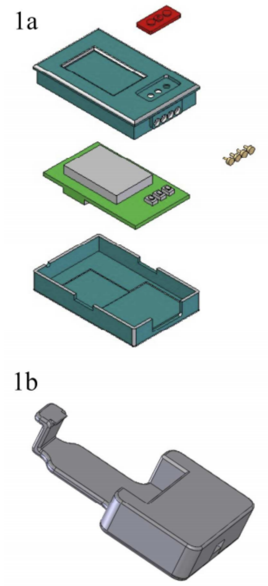

Figure 2.1: Inertial sensor node assembly and frame.

fer with no need for additional hardware this low-cost equipment serves the purpose it is meant to.

– Synchronising inertial sensor data, in this case, accelerations occurring at the spine at C7 and S1 [DAJ11a].

– The device is packaged to an appropriate size and weight, and is robust, hermetically sealed and biomechanically neutral to the athlete [DAJ11a].

– The packaging was revised during several iterations taking into account subject comfort, waterproofing (double membrane), extruded pins for electrical connection and sealed bearing micro switch actuators [DAJ11a].

– – The most relevant drivers for design were its small size and usability, whilst being waterproof. The small size minimises the effects of drag and artefact from the aquatic environment, it is comfortable for the athlete, yet large enough to be useable as a user. Generally waterproof enclosures require complicated assemblies including use of rubber o-rings and screws, instead we opted for a sealed-for-life solution [DAJ11a].

- According to [DAJ11b] accelerometers measure inertial changes at the sensor location, in typically one or more axis, are millimetres in size. These sensors enable complex body dynamics to be measured. It is well understood though that the determination of positional information is a difficult and complex task. Researchers have also used accelerometers for determining physical activity and effort undertaken by subjects. These kinematic systems have been able to offer comparable results to expensive optical-based systems.

- As stated in [M.S11] the swimsuit will integrate sensors for the measurement of several physiological and biomechanical signals; in this case focusing on ECG and respiratory movement analysis. The data obtained is mainly intended to provide tools for evaluation of high-performance swimmers, although applications can be derived for leisure sports and other situation.

- In consonance with [ASSC11] nowadays, miniaturized low-powered accelerometers and gyroscopes, embedded within wearable monitoring systems, have closed the gap between an athlete's perception and that of trainers.
  - Micro-electromechanical systems (MEMS) represent a viable alternative which, unlike many of its counterparts; can be integrated within wearable-water friendly solutions that can aid on swimming analysis, without burdening the athlete with cumbersome garments and/or equipment [ASSC11].
  - Sometimes healthcare, rehabilitation and sports gathered physiological and mechanical data through cumbersome apparatus that affected the behavior of the target individual and even constrained the range of movement [ASSC11].

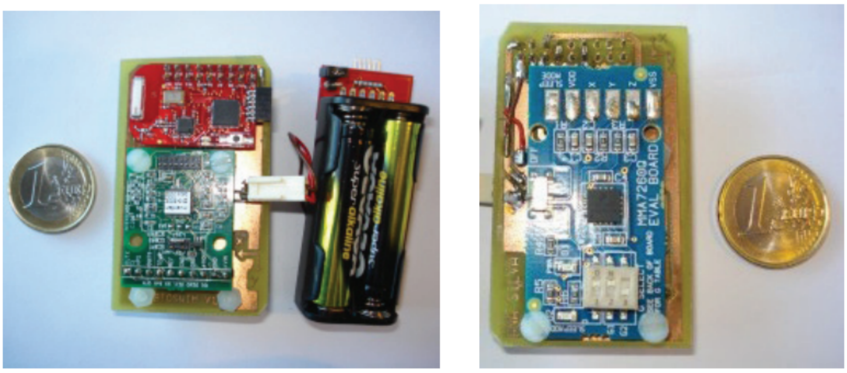

Figure 2.2: View on the measurement device.

  In 2.2, both, top and bottom, sensors utilized are MEMS equipment; micro-machined inertial sensors have a massive potential for applications within the biomedical and sports area due to their short volume, mobility, low power consumption and relatively reduced cost.
  - A wearable solution agreed upon was the combined ease of use and seamless electronic integration for a more ubiquitous signal monitoring experience. Producing an wearable elite training evaluation station, allowing the most innovative monitoring, ambulatory registration, real-time visualization and post-exercise display of both physiological and biomechanical relevant data for training (heart-rate, respiratory frequency, oesophageal temperature, sweat, arm tri-axial acceleration) [ASSC11].
  - Important repercussions are expected both for practitioners, coaches and scientists, allowing increased safety in physical activity, an augmented objectivity - and efficiency - of the elite training process, and stress-free data collection for scientific research in neuro-physiology and biomechanics of sport [ASSC11].
- The analysis of free swimming was predominantly supported by the wireless sensor technology, whereby signal analysis was capable of automatically determining factors such as lap times variations within strokes [SLA10].

- Tri-axial accelerometers were used to assemble and save data at a sample rate of 100Hz. With rather a small size and weight, performing capabilities in a wide range of temperatures, and with waterproof features. This device, settled in the upper back midway, for peak convenience and slightest drag, has theoretically the conditions to acquire useful data in this environment [SGT17].

2.3 Monitoring dashboards in swimming

The control panel is the other concern to consider. Unfortunately, throughout the swimming community, the scarcity of hardware equipment regarding biosignals measurement in the aquatic environment is evident. This influences and impacts the number of monitoring dashboard systems/software. These are several different important aspects inherent to the development of a functional easy-to-use resourceful dashboard.

- The GUI should be clean and deliberately designed to appear uncomplicated to provide a user-friendly interface [DAJ11a].
- Possible extension of the system by integration into cloud base storage, distribution and analysis can be desirable [DAJ11a].
- The capability to share assessment of an athlete by a person's own coach and state or national coaches allows athletes to train closer to home for greater periods without necessarily relying of relocating or travel to main centres for sporting career development. It is hoped potential for remote servicing and monitoring of athletes can be realized [DAJ11a].
- Tools Wise according to [DAJ11a]:
  - All client software can be developed using the Matlab™ high performance-computing environment, which has libraries for developing graphical user interfaces (GUI), peripheral communications and numerical computation [DAJ11a].

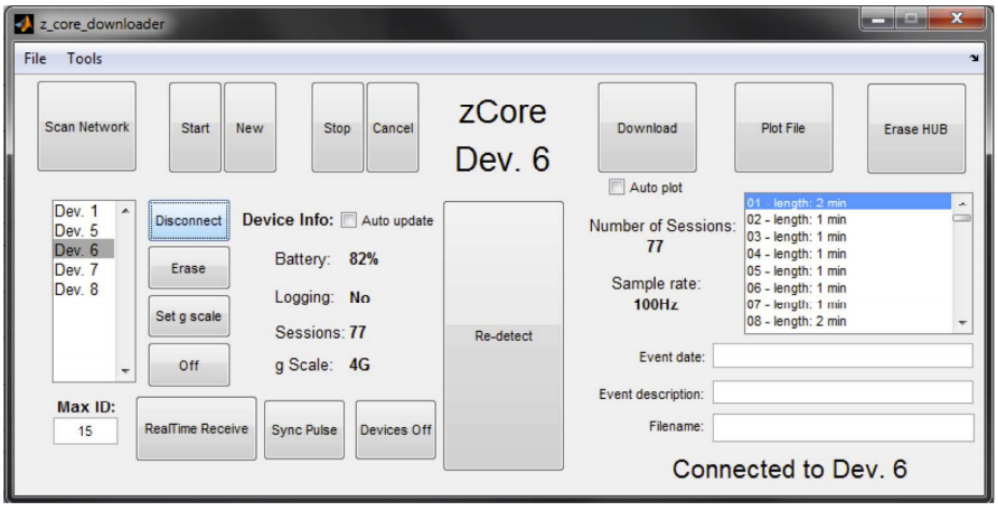

Figure 2.3: GUI for node control.

As showed in Figures 2.3 and 2.4 there is a set of functionalities worth mentioning in this dashboard that could be interesting to bear in mind for this project. The automatic detection of connected nodes, wireless node device info, wireless node control (start/stop logging, start/cancel session, sync pulse, turn off nodes), battery info, sample rate, download of data from many nodes, and real-time data collected from the device. Capabilities such as those contribute to a complete monitoring dashboard.

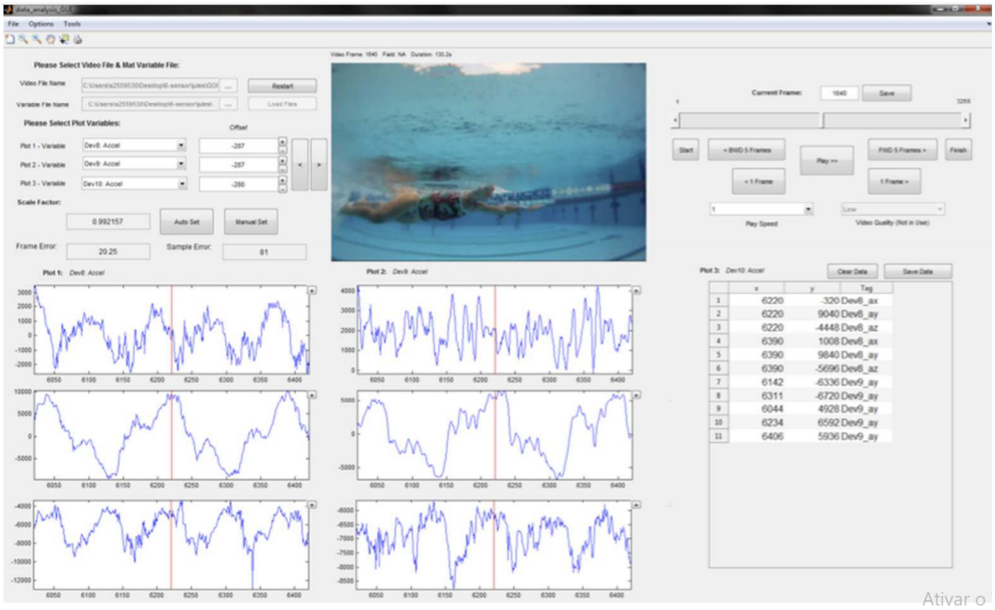

Figure 2.4: GUI output on freestyle swimming.

– Includes the Data Analysis GUI spreadsheet function and video capture, which has been synchronised to inertial sensor data, in this case, accelerations occurring at the spine at C7 and S1. Additional values can be inserted into the spreadsheet by hover and click over a particular point in a plot. Automatic insertion is carried out [DAJ11a].

- Looks towards fine-tuning of the prototype system into a useable solution for end users. This relies on the refinement of components and the development of an appropriate user interface to enable ease of data collection, analysis, presentation, and interpretation [SLA10].

- LabVIEW platform was usedfor the computer interface development, the dashboard was able to configure COM port parameters, swimmer's intel, recording, database storage of data, visualization of the streaming data, and signal strength from the device [ASSC11].

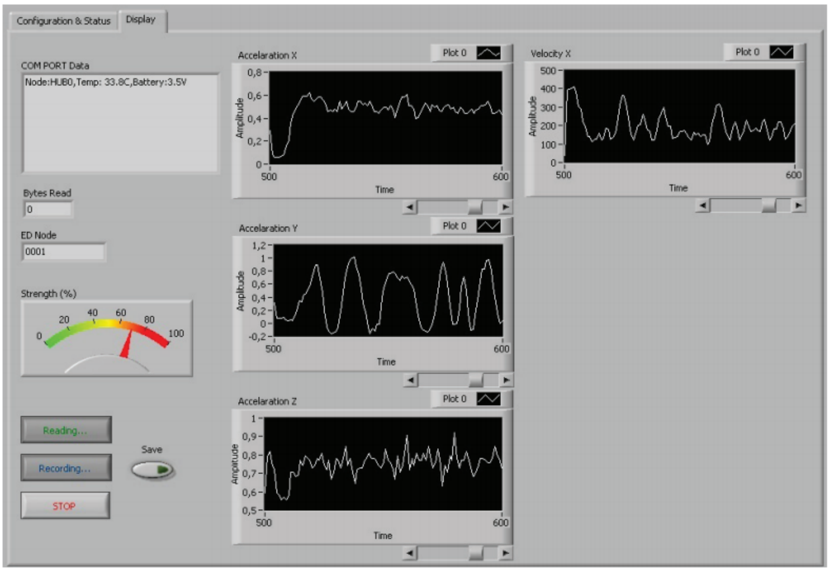

Figure 2.5: Data collection dashboard through LabView user interface.

In 2.5 some additional data is presented, like temperature, battery specification, graphs of acceleration, and velocity according to the tri-axial accelerometer are also on display. The latter is being extremely useful for our context.

- As stated in [DAJ11b], the proposed cyber infrastructure includes temporal synchronisation of all sensor platforms and synchronisation with video data. Frame creep and clock drift are important factors for recording as they become significant in only a few minutes.

  – Data processing: Algorithms for sacral data have been previously described and extension to wrist and leg mounted sensors is under development using this system to collect concurrent video and sensor data [DAJ11b].

  – Client visualization: Current methods of feedback to athletes and coaches are usually summary statistics consisting of counts, split times and times over a session(s). It is time consuming to collect, especially for squad camps and not always available for immediate feedback. A Matlab client was developed to integrate multiple sensor platforms together with video data to provide the basic functionality required of a swimming monitoring system. Two sensor platforms, previously synchronised together with video data of the swimmer are displayed [DAJ11b].

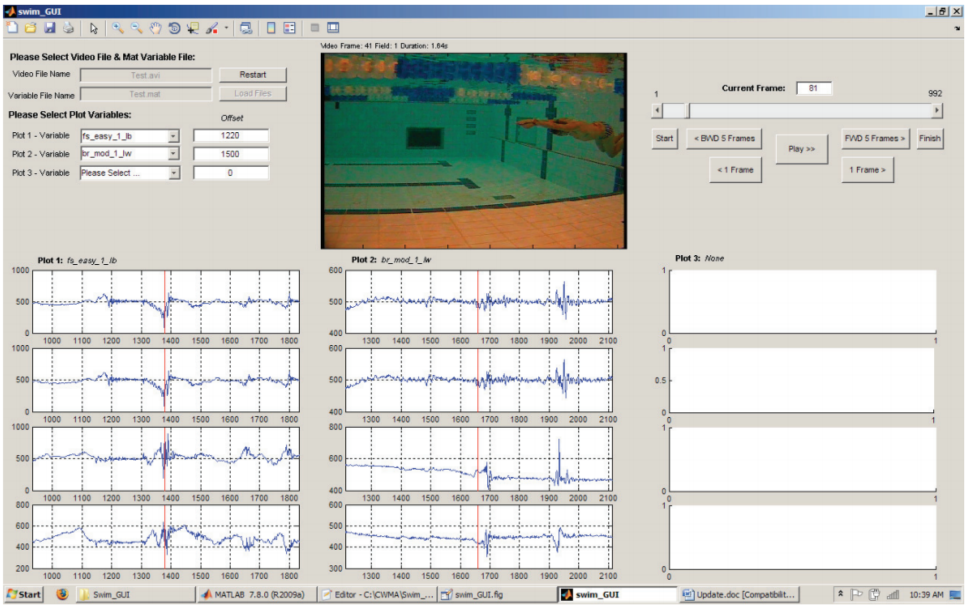

Figure 2.6: Functional dashboard prototype.

Client playback of submerged video with freeze frame and slow motion are frequently used at the elite level but, in most cases, this can be replaced with sensor data, once it is an accepted device. Algorithms embedded in the sensor nodes will provide feedback to the swimmer either as post-training session insights or during sessions such as a display on starting block or a sound signal (whistle). Hopefully, with the improvement of RF in water and real-time streaming of data to the local host and database, additional swimming users (coaches) will be taking advantage of the possibility of recovering the raw or processed sensor data together with video [DAJ11b]. Plots with sensitive accelerometer data are on display in 2.6.

- In [SGT17], the video type data, as well as statistical analysis, was loaded using Matlab. Several situations were digitized: the tapping of the accelerometer for synchronisation, stroke type of each lap, stroke count, stroke rate, push-off (last touch off the wall), first contact with the wall, entrance of the hand in the water for each stroke.

Chapter 3

Hardware development and implementation

The content of this chapter contains a somewhat more practical approach to the work. A preface of the hardware used, including all its attributes, attachments, and design.

3.1 Introduction

At this point of the report, there is a clear understanding that this work has two distinct segments. One is the hardware (measurement device) and the other the software (dashboard). Proceeding in the document, information on the type of hardware used, including the company, the assembling of the device along with some dry testing will be provided. An in-depth view of the hardware components is also due.

3.1.1 Bitalino

Bitalino was born as a university project conducted by Hugo Silva, electrical engineer at the Institute of Electrical Communication in Lisbon and was then developed by Plux-Wireless Biosignals. It is a low cost, open-source hardware single board computer designed for education, prototype development and biomedical research. [Wik21]. The BITalino was designed to be suitable for the acquisition of physiological signals. To record physiological signals, it is possible to use BITalino with the OpenSignal software or using an API. The BITalino was among the finalists of the Innovation Radar Prize 2017, promoted by the European Union, in the ”Industrial Enabling Tech” category.
The APIs are available for the following platforms and programming languages [Wik21]:

- Python
- Android
- Matlab
- Arduino
- Bonsai Library
- C++
- Objective-C
- LabView
- Java
- Raspberry Pi
- Unity

The Bitalino boards can be equipped with [Wik21]:

- Power (PWR)
- Microcontroller (MCU)
- Batteries
- Eletrodes

- Electromyography (EMG)
- Electrocardiography (ECG)
- Electrodermal activity (EDA)
- Electroencephalography (EEG)
- Bluetooth (BT)
- Temperature (TMP)
- Eletrooculography (EOG)
- Eletrogastrography (EGG)
- Accelerometer (ACC)
- Photo detector
- Button
- Led
- Digital-Analog Converter

The BITalino has several applications and can be used in many health and sports-related research works, being a small, light, and affordable peace of hardware that is available to anyone who wants to develop any kind of personal projects with biosignals.

3.2 Device's specificities

3.2.1 Device Cost

Since the financial aspect is obviously an important domain to consider, an estimation of the device cost has been made. The values shown below are strictly the prices from the BITalino store [Bit21].

- Bluetooth Block (BT): <u>20€</u>
  - Plug and play communication module with UART interface;
- Power Block (PWR): <u>15€</u>
  - Controlled voltage output and battery charging circuit;
- Microcontroller Block (MCU): <u>17,50€</u>
  - Microcontroller piece pre-programmed with the BITalino software for real-time data transmission;
- Electromyography Sensor (EMG): <u>22,50€</u>
  - Aim-built sensor for muscle action measurement;
- Electrocardiography Sensor (ECG): <u>22,5€</u>
  - Aim-built sensor to determine the heart's electrical action;
- Accelerometer Sensor (ACC): <u>22€</u>
  - Tri-axial accelerometer for movement assessement.
- Battery: <u>7€</u>

– LiPo battery 3.7V 500mAh providing 5-7h of full-on activity;

Individually, adding up all sensors and blocks, with the addition of connection cables, electrodes and considering that we will be using two EMG blocks, the costs will range between 149€ and 169€ [Bit21]. There is also a possibility of purchasing a BITlaino Kit, which contains all the mentioned above and more for 169€.

3.2.2 Device Architecture

In 3.1, shows a representation of the architecture used in on the development of the biosignal measurement device.

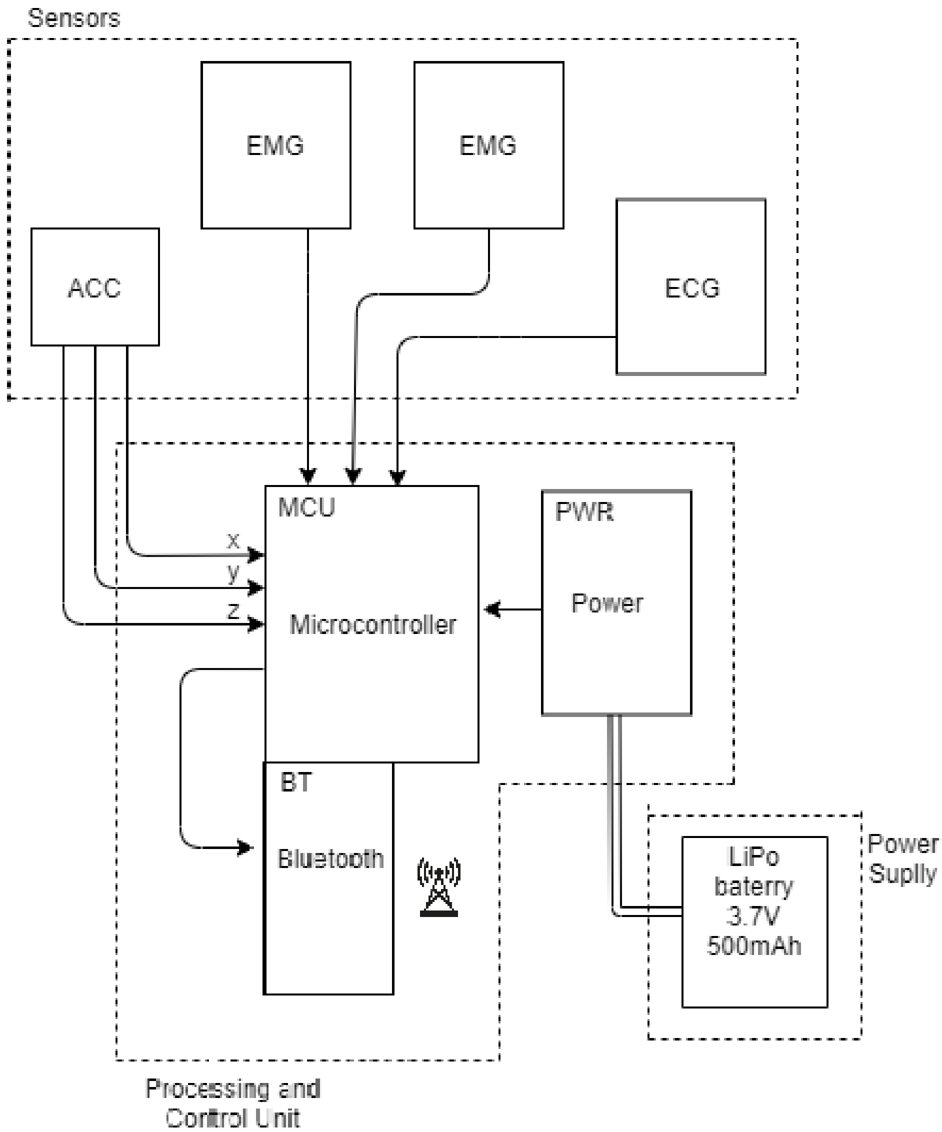

Figure 3.1: Device Architecture Scheme.

3.2.3 Device Construction

The device composed of bitalinos with MAC address 20:15:10:26:64: consists of an accelerometer, an ECG and two EMG's. The development of these individual components proceed the follows instructions:

- ACC:
  - Green coloured cable on site VOUT-X;
  - Black coloured cable on site VOUT-Y;
  - White coloured cable on site VOUT-Z;
  - Red coloured cable on site AVCC/VCC;
  - Mesh cable in place AGround/GND;

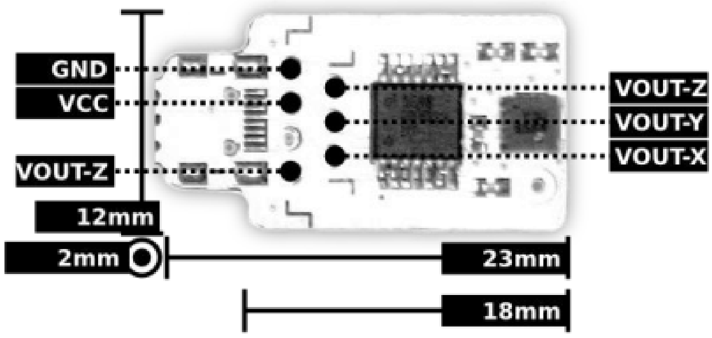

Figure 3.2: Accelerometer sensor detailed view [Bit21].

- ECG:
  - Red coloured cable on site AVCC/VCC;
  - Mesh cable in place AGround/GND;
  - White coloured cable on site VCC/2/USS;
  - Green coloured cable on site VOUT/A3;

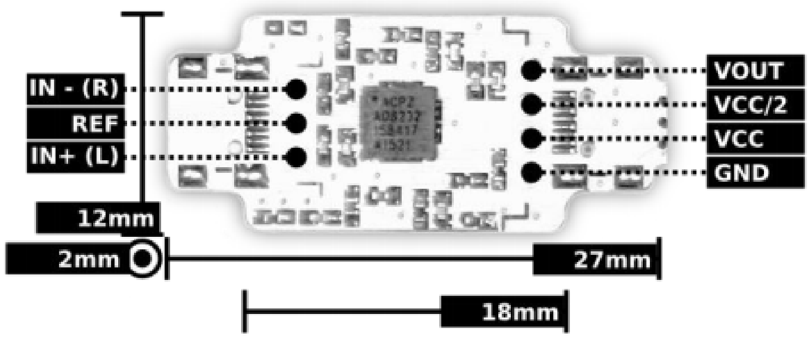

Figure 3.3: Electrocardiography Sensor detailed view [Bit21].

- EMG:
  - Green coloured cable on site VOUT/A1;
  - Red coloured cable on site AVCC/VCC;

- White coloured cable on site VCC/2/USS;
- Mesh cable in place AGround/GND;

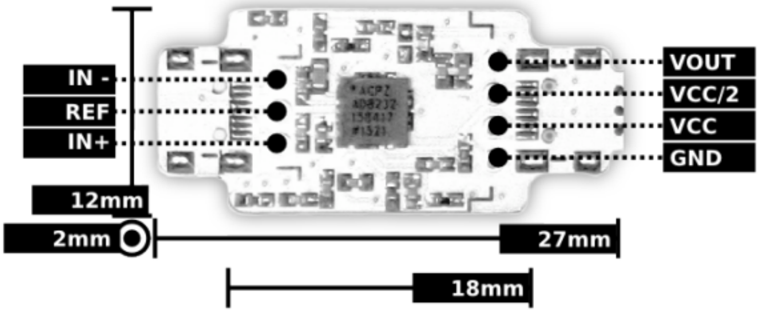

Figure 3.4: Electromyography Sensor detailed view [Bit21].

Other essential elements that are parte of the device as a whole are:

- PWR (Power unit)
- MCU (Microcontroller)
- Battery 3.7V 500mAh
- Electrodes

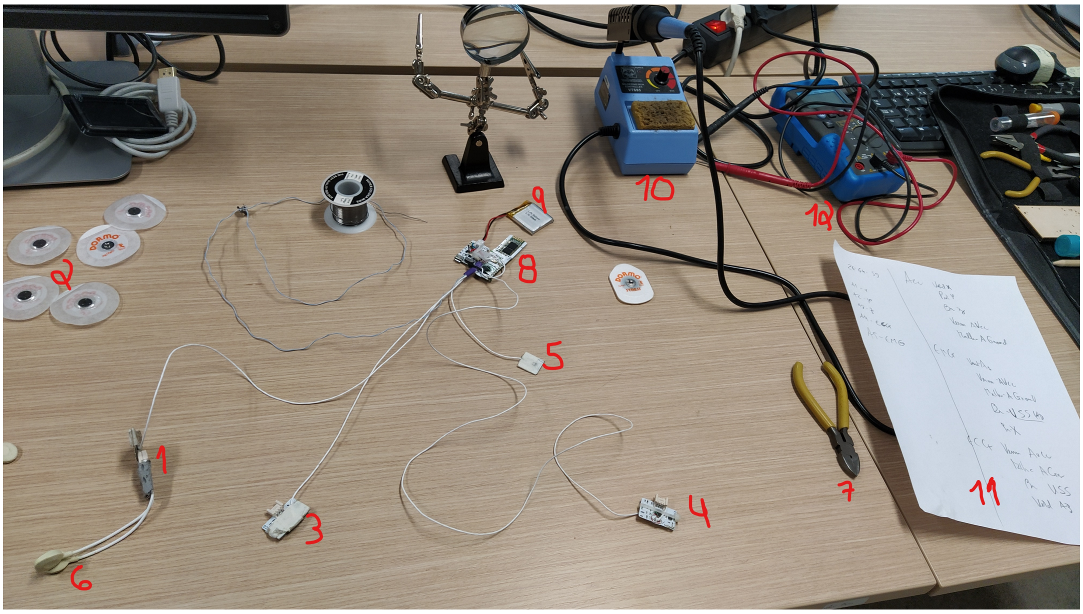

Figure 3.5: Device and worktable shot.

In 3.5 there is a photograph taken during the last days of the device construction. Below, the name of each component indicated in the photograph is listed.

1. EMG sensor;
2. Electrodes;
3. ECG sensor;
4. EMG sensor;
5. ACC sensor;
6. Electrode cable;
7. Pointed pliers;
8. Main components (MCU, PWR, BT);
9. Battery;
10. Soldering machine;
11. List of connections and attachments;
12. Multimeter device;

3.2.4 Device Weight

Another parameter that needs to be taken into consideration, is the weight of the entire, device fully connected device. This equipment weighed **61 grams**, which is more than acceptable for the context of the purpose needed.

3.2.5 Placements Spots

The present segment shows where the device and its sensors may be applied. This observation was reasoned on the wire length available, as well as on where the measurements would be more reliable and valuable. Research studies previously conducted also refer to the locations suggested below. Wrist and ankle are also referred. Following, some of the locations mentioned are presented:

- Main components: Back neck under the cap;
- ECG sensor: Heart area (left region of the chest) with three electrodes;
- EMG sensor: One on the thigh area of the leg (quadriceps)with two electrodes, and the other on the arm (biceps or triceps region) with also two electrodes;
- ACC sensor: Centre/middle of the back;

Chapter 4

Software/dashboard development and implementation

This chapter aims to make a detailed approach to what was developed, from the technologies and tools used to every single implementation, as well as a brief explanation on why each was decided to be included on this dashboard.

4.1 Introduction

In the making of this dashboard, many choices were made, mainly inherent to what could be extracted and calculated from the raw data measured by the sensors, what made sense to be covered within this environment but also, what kind of a more heavy computing calculus and processes could eventually overflow the system and, of course, the main concern, corrupt and compromise the data. So, firstly will be addressed the bitalino python library, how it was used, and with what purpose; then the power BI platform on how it was essential to connect the data processing to data visualization. Later on, the core matter, all the functionalities, and features developed for a more wholesome and efficient experience with the dashboard.

4.2 Bitalino Python API

Succeeding the intricate construction of the biosignal measurement device as well as the study and thought on how to apply it, comes the development of its respective data output visualization. To advance, a connection link is needed between the measurement and transmission of the data and the receiving end, the computer, where the processing and imagery occurs. Thus, the Bitalino (r)evolution Python API provides the necessary tools to interact and explore the device's capabilities. Nevertheless, other support documentation is also available for development in other technologies and languages; C++, Android, and unity are some of the examples. Firstly, the dependencies need to be taken into account. The installation of a compatible version of Python, numpy, pySerial, and PyBluez are strict requirements for a smooth and successful working environment while developing from the bitalino device.[GRa21] Still, another useful information for the end-user is the fact that being the connection and transmission of the data via Bluetooth, the operative system used (Windows) in this work required credentials to access the bitalino's data. The password is (1 2 3 4).

Hence, through installing the bitalino API package, the implementation can start. Following, are some of the functions used and altered to serve the purpose intended.

- **Mac Address:** A media access control address is an identifier assigned to a network interface controller. The device with the *macAddress = "20:15:10:26:64:59"* is the exclusive identifier of the bitalino compound. This information is surely crucial.

- **Battery Threshold:** Values for the electric potential may vary between 0 and 63, corresponding to respectively, 3.3 volts, and 3.8 volts. Was opted for the minimum value 0, because it showed more promising results on testing also being that the battery used was 3.7 volts.

- **Analog Channels:** This function permits each channel to be acquired. It can return lists, tuples, and also, arrays of ints. The original matrix, not pre-processed would look like the following.

```
=================  ========= ========= ========= ========= ======== ======== ========
Sequence Number*   Digital 0 Digital 1 Digital 2 Digital 3 Analog 0 Analog 1 Analog 3
=================  ========= ========= ========= ========= ======== ======== ========
0
1
(...)
15
0
1
(...)
=================  ========= ========= ========= ========= ======== ======== ========
```

Figure 4.1: Original data output matrix.[GRa21]

```
analogChannels = [0, 1, 2, 3, 4, 5]
                 [A1,A2,A3,A4,A5,A6]
                 [x,y,z,ECG,EMG,EMG]
```

Figure 4.2: Respective data output.

In 4.2 it is shown the attribution of each respective sensor data to one analog channel. All these values are raw data measured by the sensors being 'x' the x-axis, 'y' the y-axis, and 'z' the z-axis of the tri-axial accelerometer sensor; next, the 'ECG' referring to the ecg sensor and lastly, both emg sensors. So, *analogChannels = [0,1,2,3,4,5]* were the interest, also to rule out the digital channel data, which wasn't needed.

- **Sampling Rate:** The sampling rate is the sampling frequency in hertz. It returns the data type int varying its value between, 1, 10, 100, 1000; 1000 is the recommended amount to use.

- **Number of Samples:** The number of samples is a variable that defines how much data is acquired per iteration. Each measurement can vary between, 1, 10, and 100, being the recommended. So, if this variable is set to 1 it would be received data like [575,575,0,63,63], a list of ints, each of these values regarding each sensor calculation, as explained before. If set to 10 or 100, there would be shown 10 or 100, depending on what was defined, lists of ints, meaning a list of lists, in each iteration. Also, requiring a low number of samples (e.g. nSamples = 1) may be computationally expensive.

Concerning Power BI streaming ceiling on the rate of data ingestion, five requests per second, the amount and accuracy of data viewed in the dashboard is not compromised due to the fact that the bitalino can't overpass three or four iterations per second.

- **Run Time:** The runtime is just a simple function to control the time on which the device is measuring and sending data. For the intended purpose, it was defined to stop in an hour, although tests regarding the autonomy of the battery reached near 5 hours on full activity.

4.3 Power BI

Power BI is a business analytics service tool from Microsoft released on July 24, 2015. The goal of Power BI is to provide interactive visualizations and business intelligence capabilities with a simple interface for end-users to create their reports and dashboards.[Mic20]

A specific tool of Power BI is streaming in real-time. The capacity of real-time streaming of data into an easy-to-use, clean, and somewhat interactive desktop in a fairly uncomplicated way to achieve the goal required is one option very much on the table. Additionally, with Power BI's real-time streaming, you can stream data and update dashboards in real-time. Any visual element or dashboard created in Power BI can present and update visual elements and data in real-time.[Mic20] Data is also pushed to the Power BI service with a streaming dataset, but with one significant difference: Power BI only keeps the data in a temporary cache that expires rapidly. Temporary cache is only used to display visual elements that have a limited history, such as a one-hour line graph.[Mic20] In reality, streaming data sets and the corresponding streaming visual elements are most beneficial in circumstances where the time between when data is sent through push and when data is presented must be as short as possible. Furthermore, best practices suggest that data be delivered in a format that can be visualized without further aggregation.[Mic20] [Mic20]

In 4.3 on the streaming column, there is displayed some useful information about limitations using this platform, emphasis on the maximum rate of data ingestion of 5 requests per second. This will somewhat restrain the amount of data that can be streamed to the dashboard.

Capability	Push	Streaming
Dashboard tiles update in real-time as data is pushed in	**Yes.** For visuals built via reports and then pinned to dashboard.	**Yes.** For custom streaming tiles added directly to the dashboard.
Dashboard tiles update with smooth animations	**No.**	**Yes.**
Data stored permanently in Power BI for historic analysis	**Yes.**	**No.** Data is temporarily stored for one hour to render visuals.
Build Power BI Reports atop the data	**Yes.**	**No.**
Max rate of data ingestion.	**1 request/s 16 MB/request**	**5 request/s 15 KB/request**
Limits on data throughput	**1M rows/hour**	None.

Figure 4.3: Features of streaming data real-time with Power BI. [Mic20]

The connection between the data processing python script and data display on Power BI was made through a Rest API with one unique URL.
REST_API_URL ="https://api.powerbi.com/beta/2b003019-7bb5-4904-a867-5651abbd358e/..."
So, encapsulating the rest API and a data file json with the processed calculated data in a request it is established a direct link.

```
req = requests.post(REST_API_URL, data_json)
```

Figure 4.4: Connection request with processed data.

4.4 Applied models and algorithms

In this section will be highlighted the features and functionalities developed to reach this dissertation's intended purpose. Not only the data processing to achieve certain results but also some pre-processing of the raw data inputs measured by the sensors. Each specific feature was discussed and recommended by Professor Daniel Marinho that is an expert in swimming and in sports science.

4.4.1 Real-time data models

The following segments of this document will address the fundamental computational development applied to carry out an informational, useful, and valuable dashboard to aid and support swimming.

4.4.1.1 EMG sensor based data

This easy-to-use sensor measures and emits raw data outputs with a high signal-to-noise ratio through muscle activation. Such triggered by bioelectrical signals of very low amplitude sent from motor control neurons in the brain to the muscle fibers.

$$EMG(V) = \frac{\left(\frac{ADC}{2^n} - \frac{1}{2}\right).VCC}{G_{EMG}}$$

$$EMG(mV) = EMG(V).1000$$

$VCC = 3.3V$ (operating voltage)
$G_{EMG} = 1009$ (sensor gain)

$EMG(V)$ – EMG value in Volt (V)
$EMG(mV)$ – EMG value in millivolt (mV)
ADC – Value sampled from the channel
n – Number of bits of the channel[1]

Figure 4.5: Electromyography transfer function.[Bit21]

In 4.5 is presented the math function that transforms the senseless raw output to readable and usable data in volts. This unit of electric potential difference allowed some future applications, which in this case were always represented in millivolts because of the low potential energy transmission, instead of the official unit volt. Also, the 'n' value, number of bits of the channel in the image was defined as six bits, on account of the last two analog channels sampling using 6-bit resolution, which is responsible for the two EMG sensors. [Bit21]
Following are itemized the explicit data visualized in the dashboard.

- Signal amplitude:

  After the application of the math function mentioned above, this data is rounded by three decimal numbers and now is in format to be viewed in the Power BI dashboard. At each iteration, the values are measured, then received, then processed, and then sent to the dashboard for visualization purposes.

- Maximum contraction percentage:

  This model is applied equally to both the EMG sensors available. After the pre-processing and data structuring, for this feature, it's firstly identified the highest single value registered. And then, in the consecutive process, a percentage calculation is done, by dividing the number of times that this high value occurs by the total number of occurrences and then multiplying the result by one hundred. The outcome is rounded by two decimal places, and ready to be sent to the Power BI platform.

4.4.1.2 ACC sensor based data

This user-friendly sensor measures and transfers similarly to the one before, raw data outputs through microelectromechanical systems and three cartesian coordinated axes.

Movement generates acceleration that can be transformed and interpreted into numbers representing kinematic and biomechanical episodes.

$$ACC(g) = \frac{ADC - C_{min}}{C_{max} - C_{min}} \times 2 - 1$$

$ACC(g)$ – ACC value in g-force (g)
ADC – Value sampled from the channel
C_{min} – Minimum calibration value[1]
C_{max} – Maximum calibration value[1]

Figure 4.6: Accelerometer transfer function.[Bit21]

In 4.6 is once more a math function that is responsible to convert the meaningless unprocessed data acquired from the sensor to information of several potential uses. This conversion returns g-force values (1g = 9.8 m/s squared) which are later on converted to simple acceleration in the same unit. In regards to, minimum and maximum calibration values, those were set by slowly rotating the accelerometer 360 degrees to compel the sensor to intersect the gravity-constrain -1g and 1g in each ax.[Bit21]
At this point, the raw data measured by the three-axial accelerometer is converter to an acceleration unit. Each of the axis values is individually assessed and passed through. Then with each acceleration in each respective ax, it is calculated the acceleration regarding the three-axis at the same time. At this moment, the acceleration is being measured regarding the three directions (x,y,z).

- Instantaneous velocity:

  Since the acceleration in all the axes is calculated, the next step is to determine the instantaneous velocity. To do so, the algorithm was developed taking into consideration, the possibility of having no acceleration in a period of time which means that the velocity is constant; the possibility of negative velocities which in this context were disregarded; also values were normalized/standardized and rounded in three decimal places. Lastly, the velocity at a certain point is calculated through the difference between the final acceleration and the initial acceleration times the difference between the final acceleration and the initial acceleration. This process is executed at each iteration to determine at each time there are measurements of the respective instantaneous velocity.

- Average velocity:

  Concerning the average velocity, since the model developed before does most of the calculations needed with all its minuteness and detail, the next step is a fairly simple one. The average velocity is figured through a mean function regarding the previously determined values of the instantaneous velocity.

- Maximum average velocity percentage:

  In the same way, for this feature, it is used the processed values were determined earlier. So, firstly, it is pinpointed the highest particular value recorded until then and subsequently, a percentage calculation is made. By dividing the number of times that this high value occurs by the total number of occurrences and then multiplying the result by one hundred, the outcome is produced. Such that is also rounded by three decimal places, and then sent in the json file to the Power Bi dashboard to be visualized.

4.4.1.3 ECG sensor based data

This convenient sensor measures and transmits identically to the previous ones the crude data outputs with also a high signal-to-noise ratio and both on and of person usage. Heartbeats are activated by bioelectrical signals of pretty flat sufficiency produced by cells within the heart. Electrocardiography (ECG) allows the translation of these electrical signals into numbers, permitting them to be used in a broad collection of purposes.

$$ECG(V) = \frac{\left(\frac{ADC}{2^n} - \frac{1}{2}\right) \times VCC}{G_{ECG}}$$

$$ECG(mV) = ECG(V) \times 1000$$

$VCC = 3.3V$ (operating voltage)
$G_{ECG} = 1100$ (sensor gain)

$ECG(V)$ – ECG value in Volt (V)
$ECG(mV)$ – ECG value in millivolt (mV)
ADC – Value sampled from the channel
n – Number of bits of the channel[1]

Figure 4.7: Electrocardiography transfer function.[Bit21]

In 4.7 is the scientific function in charge of commuting the pointless data measured by the sensor to an ideal form of data that can be afterward useful. The unit returned from the calculations in millivolts as is the EMG sensor one, although in what comes to the 'n' value it was used ten bits. The sampling used was a 10-bit resolution due to the fact that, as mentioned before in this document, the ECG data is the fourth element in the analog channel. [Bit21]

4.4.2 Post-time data models

Another couple of features added were the post-time data appraisal. Although several studies indicate that this type of observation is exhausting, laborious, and time-consuming, and ultimately not worth it, others also, show interesting and beneficial results on using this kind of supportive technology. Review and correct some punctual technical and physical details in specific segments of the practice would be a plus. In this train of thought, it was developed two tools that could be used by both coach and swimmer to scrutinize any doubts or small problems that happened in practice, and that could be later on rectified.

4.4.2.1 Data saving in csv

The process of saving the measured data is simple and not computationally demanding. Being so, the data that is calculated/processed after its measurement is sent to the Power BI platform as well as a CSV file. Due to, the CSV python library, data is easily written and saved so that any time that is a misunderstanding or there is any need to review the acquired values at any specific given time, there is a direct way to do it. This file is located with the processing data python scripts so that it can be consulted anytime.

4.4.2.2 Screen recording

Another functionality that was interesting to be taking into account is the recording of the screen upon data assessment. Developed with the support of cv2 and pyautogui python libraries, the capability and the possibility of having a full HD avi type file to further examine and analyze the behavior of the athlete during its practice is a valuable asset. Once again, this file comes in the same folder as any other project script for a easy access.

4.5 Results

4.5.1 Real-time data product

This section relates to the product of the models and calculations done from the sensors for a visualization perspective. A thorough explanation of each particular functionality is addressed.

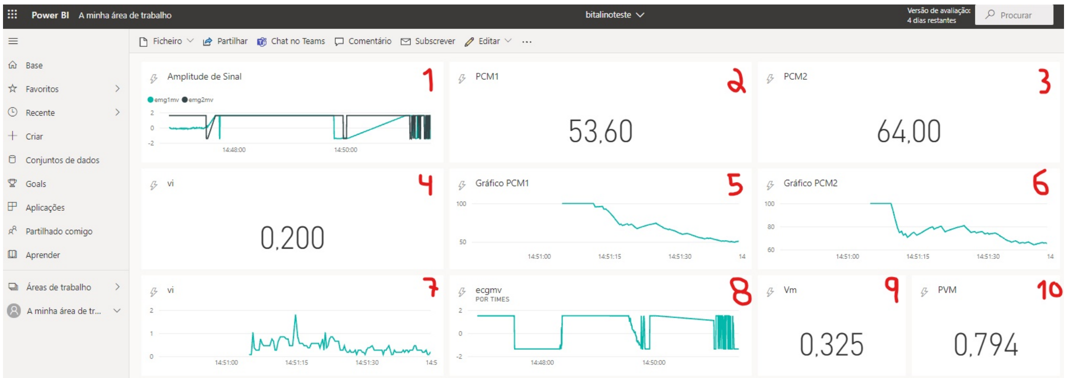

Figure 4.8: Dashboard display.

In 4.8 is a screenshot taken whilst the data measurement and posterior processing is taking place. These tiles can take different forms on presenting the data from, several types of graphs to a simple card format. The charts need a 'x' value which would surely be the time/clock. Following is a detailed approach to each one of the ten tiles used to display the treated data points.

1. **EMG signal amplitude graph:**

   This tile regards both the two EMG sensor data. There is a line graph with both a title and subtitles, to ease data comprehension. The x-axis concerning the time on each data point. Also, values may only vary from two to minus two in millivolt (mV).

2. **EMG number one maximum contraction percentage value:**

   This card-type tile contains data from one EMG. This data slowly changes on each iteration being that is a percentage. Also, it was defined to always use two decimal places.

3. **EMG number two maximum contraction percentage value:**

   Similarly, this card-type tile contains data from the other EMG sensor. This data slowly changes on each iteration being that is a percentage. Also, it was defined to always use two decimal places.

4. **Current instantaneous velocity:**

   From the accelerometer sensor data, it is extracted the instantaneous velocity to a card-type tile. Typically it also changes on each iteration and slowly being that speed does not increase or decrease suddenly, only in the case of a start or a stop, in this case from the part of the athlete. Further, it was established a display of three decimal places for a more precise appraisal. The data unit is meter per second.

5. **EMG number one maximum contraction percentage graph:**

   This is related to the data shown in item two of this list. This line-graph is using the data of the card above it as its y-axis values and its respective time as the x-axis. This data representation offers a different outlook on the information for both athlete and coach to analyze.

6. **EMG number two maximum contraction percentage graph:**

   This is related to the data shown in item three of this list. This line-graph is using the data of the card above it as its y-axis values and its respective time as the x-axis. This data representation offers a different outlook on the information for both athlete and coach to analyze, and possibly a more insightful appraisal.

7. **Instantaneous velocity graph:**

   As the tiles before, this line-graph based is the visualization of the previously calculated and shown instantaneous velocity by its respective time upon measurement. Values often max out before the 2 m/s, unless an extreme movement not swimming-related is done.

8. **ECG values graph:**

   The only tile about the ECG data is this line graph. This chart functions in the same way as the others regarding the x-axis as the time on measurement. Also, calculated values obtained are strictly between two millivolts and minus two millivolts.

9. **Average velocity value:**

On the accelerometer-derived data, it is still determined the average velocity. This data is displayed in a card tile and with three decimal places for a more precise overview.

10. **Maximum velocity percentage value:**

    Lastly, and also through ACC sensor data calculations, it is displayed in percentage, the maximum velocity value, with three decimal numbers.

4.5.2 Post-time data product

In this segment, the results of the applied features regarding post-time data will be addressed. How to access or locate these files as well as their appearance and explanation are detailed in this section of the document.

4.5.2.1 Data saving in csv

Firstly, concerning the saving of the processed data, was opted to maintain the data list sequence previously used in the json file, such that is the data file that is used in Power BI to present the data from.

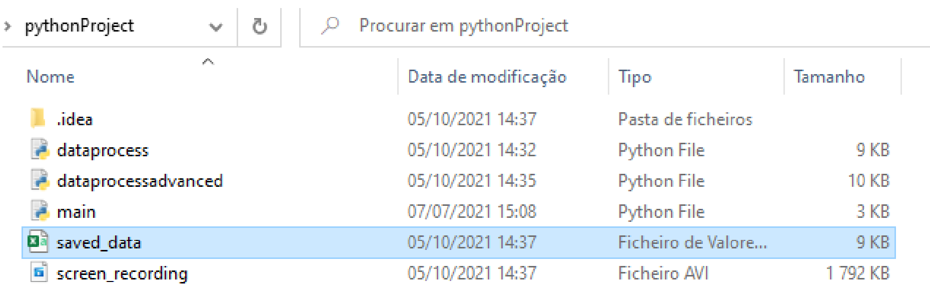

Figure 4.9: Csv file with acquired data.

So, in 4.9 is established the "saved_data" file regarding this processed data, in the same directory as the others.
In 4.10 is visualized the structure composition of the data, with a header in the first row and each iteration data with its respective time on which was measured.

4.5.2.2 Screen recording

Secondly, the screen recording feature was in fact developed through several screenshots put together in five frames per second video.
In 4.11 is the avi file with the screen recording data.
In 4.12 is a screenshot of the recorded video. This file can occupy a bit of memory because it is a 1920 x 1080 video. However, each time the "dataprocess" python script is run the previous video is replaced with the new, maintaining control of the memory used.

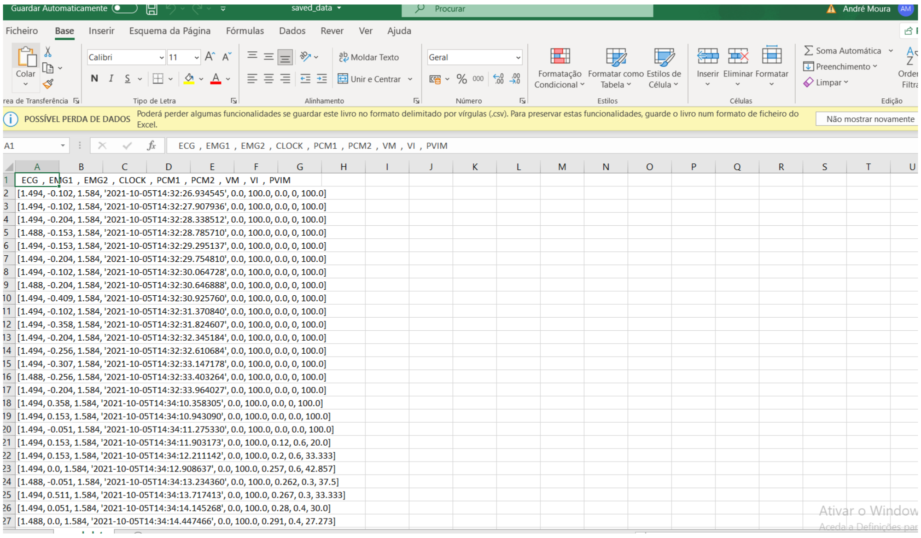

Figure 4.10: Data organization within the file.

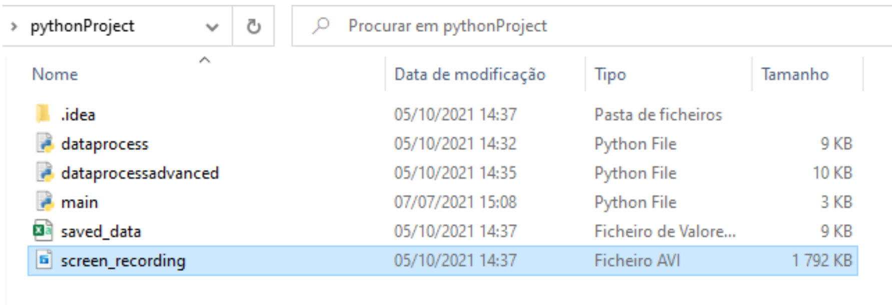

Figure 4.11: A video with the screen recorded data.

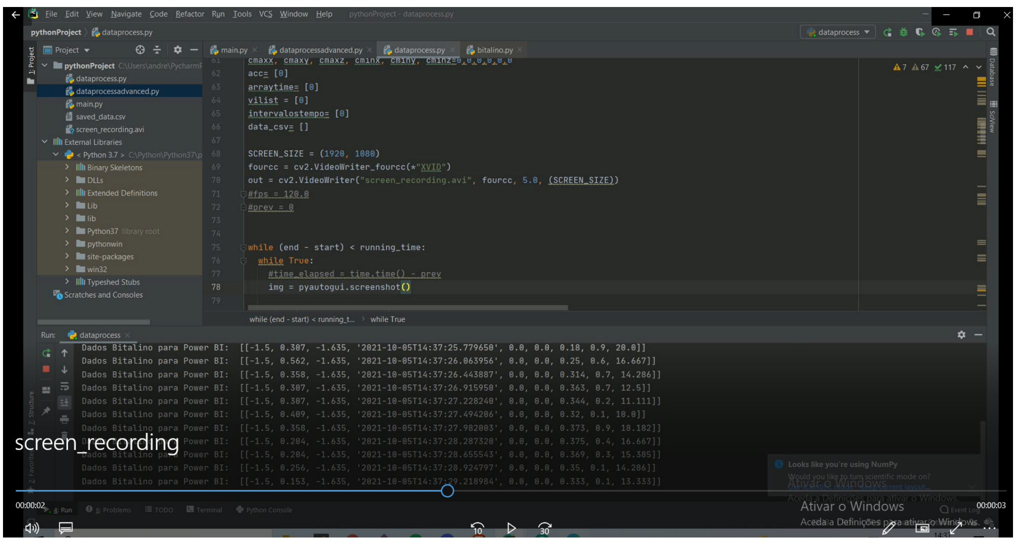

Figure 4.12: Image example of the recorded video.

Chapter 5

Conclusion

This chapter addresses all the main conclusions, from achievements and developed outcomes to the future work. As mentioned, throughout an expected complete assessment of the current work conducted on the approached area, the competitive swimming world lacks monitoring devices and software that can be used to help swimmers and coaches in swimming training. Some of the most interesting papers addressing this topic have proven that the use of this equipment is undoubtedly an added value to the swimming performance and recovery of the athletes. A comfortable and affordable biosignals measurement device together with an assistive user-friendly dashboard software can provide several sensor-type (ECG, ACC, EMG) data. Hopefully, this real- and post–time data visualization capability will impact and enhance swimming efficiency and gains, training methods, and healing processes.

5.1 Contributions and Achievements

The measurement device features and characteristics will come to play a huge part in the upcoming data collection and in its daily use in the competitive swimming environment. Waterproof, botherless, comfortable, convenient, light-weighted, and inexpensive were predominant concerns that shaped the design of this aquatic environment type of gear. So, this device aims to aid teams around the country regardless of their size or financial position. In what comes to objectives, I think the work covers a respectable amount of features and functionalities that were proposed to be addressed. Although it would be interesting to ascertain another set of capabilities there weren't able to be implemented in this system. Such as the calculation of beats per minute through the ECG as well as some more complex information, like, stroke identification, turn identification among others. Nevertheless, these last ones would need to be heavily tested to achieve, which are related to another issue encountered; the inability of on-water testing. With this work, I truly think both in concern to hardware and software aspects that this system is fairly thorough and sheer and it should be further developed and on-water tested as said before. A starting point to instill these technologies in the swimming community nationally is the maybe near.

5.2 Future Work

In future work, it could possibly be undertaken some of the on-water testings mentioned, but also the calculations for BPM, a more direct and not restricted system in what comes to the visualization of the processed data, amp up the number of samples so the results would be more accurate and reliable. Some deadlocks and difficulties were naturally encontered. One of them has to do with the current Covid-19 pandemic situation, that is affecting directly the on-water-testing of the planning stage, because of the closure of the Municipal Pool of Covilhã. The other is related to the data transfer capability of the Bluetooth 2.0 through water and distance coverage/reach which through research was found to be a challenge although the placement spots of the bluetooth device were set taking into account this detail..

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