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Investigation Report: Study of scientific articles on the theme of the detection of simple physical activities using a communicating embedded device

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*Abstract*-- The objective of this paper is to analyze, interpret and draw conclusions from the study of about 15 research papers with similar topics. The topics can be summarized by the study of the accuracy of pattern matching to classify everyday sports activities using acceleration and angular velocity signals recorded by a wearable module.

*Index Terms*-- Accelerometer, Algorithm, Embedded sensor, Classification, Detection, IoT, Activity recognition

# Introduction

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the development of new technologies, and more specifically of communicating embedded systems, it is becoming easier to develop embedded modules. Despite the relatively limited computing capacity of microcontrollers compared to modern computers, they still allow the development of simple solutions by integrating various environmental sensors. Within the framework of the Electronic Sensor Networks course, it was necessary to carry out a study of documents and scientific journals in connection with the final project. The final project is defined as the implementation of a system with an ESP32 microcontroller (ESP32-WROOM) at its heart, a system that also embeds an OLED display (SSD1331). This contraption will have to be able to collect and process the data of an Inertial Measurement Unit (IMU) (MPU 9250 in our case) which integrates an accelerometer, a magnetometer, and a gyroscope, each one articulated around 3 axes. This autonomous module will be embarked on the person and will have, thanks to a specific algorithm, the capacity to categorize the physical activity carried out by the person among daily actions (at rest, walking, running, sitting and more eventually). To achieve this project, it is necessary to carry out a study based on scientific papers whose projects are similar to the one proposed here at the university. In this document will be exposed the study of about fifteen scientific journals from scholar.google.com.

After analysis and explanations, conclusions will be drawn about the relevance of the choices, techniques and parameters implemented in these studies. First, the hardware used in these studies will be discussed, including the electronic modules and sensors used. Then, the software part will be reviewed, with all the acquisition, preprocessing, qualification and algorithm used.

# Technical study

## Hardware and acquisition part

Within the framework of the project, the module used as a basis for our work is imposed, but it remains interesting to see the solutions that have been implemented in the different studies. We can notice three main hardware approaches. First of all, modern smartphones are all equipped with an IMU. This one normally allows to know the orientation of the phone or to play the role of a pedometer. The studies [6] and [13] are based on an Android smartphone for data acquisition and processing.

The second type of acquisition apparatus corresponds to the use of a commercial solution embedding the necessary sensors already ready, then to do the processing part via a PC for example, [10]. These solutions offer several advantages: they are ready to use and do not require special knowledge of electronics. All that is required is to set the parameters of the device correctly (sampling frequency, ADC resolution, communication protocol, etc.). Moreover, they have been designed for the sole purpose of acquiring health data and are therefore optimized for such use. However, there are some negative points too; we don't really have control over the hardware, and we have to make do with what the manufacturer provides us. Finally, the third solution used, and which is the one I should develop for the project, is to build and assemble the acquisition module. We start from a programmable board based on an Arduino as in the studies [2], [9] and [11], or, like us, from an ESP32 like in [4] or any other programmable board gathering the required hardware capabilities.

Then, even if it is quite possible to rely on a single inertial unit for our project, several studies equip the person testing the equipment with several sensors, placed at different places on the body, like the study [12]: a sensor on the thigh and another on the wrist. This allows to have several data sources on two different physical areas, and consequently increases the reliability of the system, but greatly complicates the development of the solution.

However, most studies use only one accelerometer, and obtain quite satisfactory results. We notice that the works [2] and [4] use the MPU6050 reference inertial unit, very similar to the one used for my project. This chip embeds an accelerometer and a gyroscope, each on 3 axes, and a block allowing to realize the communication via I2C bus. The MPU9250 we will be using also integrates a magnetometer and supports the SPI communication protocol which is much faster than I2C. These models are very popular with electronics enthusiasts. They are usually sold as small ready-to-use modules, I myself have used them in the past. All this shows that you don't necessarily need professional equipment to get a usable dataset for your application.

Once the sensor has been chosen, the question of the collected data must now be addressed: how to transfer these data between the sensor and the processing part (PC, smartphone, or on-board controller), which parameters to use for the IMU, at what frequency to sample. The majority of the research papers unfortunately do not specify the communication protocol used, but for [2] and [4], the data are transferred via I2C, an obvious choice since the MPU6050 only has this interface. Concerning the study [5] using a commercial sensor, it communicates via Wi-Fi for example. It depends on the specificities of each acquisition board (Wi-Fi, Bluetooth, USB...).

After that, it is necessary to configure the frequency at which we will collect the data. For the physical activities that we are trying to determine, according to [3] and [11] and the research that I was able to conduct on the Internet, after performing a Fourier transform on the signal of an IMU we get:



Figure 1

On Figure 1 above is represented the FFT (Fast Fourier Transform) of an acceleration signal of an IMU parameterized with a sampling frequency of 100Hz. We notice that most of the energy is contained between 0Hz and ~20Hz, and the presence of a symmetry at 50Hz: there is a repetition of the spectrum every 100Hz. To avoid any spectral folding, it is therefore very important to respect the Shannon-Nyquist criterion: the sampling frequency must be greater than twice the maximum frequency component present in the signal (here about 20Hz).

This is the reason why the vast majority of studies use a sampling frequency of 50Hz or more; to be able to have the 0-20Hz band usable without risk of spectral aliasing. Moreover, according to [15], if we choose a sampling frequency lower than 50Hz, the system is more sensitive, 50Hz seems to be a good compromise in our case.

Another solution is to use a higher sampling frequency, such as 1.5kHz in the study [1], and then use a low-pass filter (in this case, a 4th order Butterworth filter, fc = 15Hz) in order to select only the frequency band of interest. However, this increases the complexity of the system. With our MPU9250, the maximum sampling frequency is 1kHz for the accelerometer and 8kHz for the gyroscope (8kHz is practically impossible to obtain in practice, if we collect only the gyroscope data, the maximum sampling frequency is ~7kHz). However, it is possible to set the cut-off frequency of the MPU9250's internal low-pass filter using specific addresses between 5Hz and 1.13kHz.

Concerning the Analog to Digital conversion, this aspect is not often mentioned in research papers. In most cases, the sensor already embeds an ADC (in general, of 16bits). It is also possible that the sensor does not embed an ADC, as is the case in the study [11]. Here, the acquisition card (which also incorporates an Arduino to acquire the data and transfer them via radio communication) integrates a 12-bit ADC). The dynamic range of most accelerometers and gyroscopes used has the ability to be parameterized. The problem here is that there does not seem to be a standard where this dynamic range value is specified... It depends greatly on the technical characteristics of the components used. To determine this parameter, I would have to do some testing in due course and see which one seems most appropriate for the project.

After defining the frequency at which we need to acquire the signals, it is necessary to set a period of time over which to acquire the data; we cannot determine physical activity on a single point, we need to record the sensor values over a defined time and then work from this sample. According to [14], a 6-second sample is sufficient to determine activity. The paper [12] uses a period of 10s, which is of the same order of magnitude. We deduce that a period of 10s seems to be suitable, to be verified in practice.

## Physical positioning of the sensor

It is crucial to determine the ideal position where to install the sensor on the person's body. First of all, if the sensor is not well positioned, the data collected may be unusable, either because the signal variations will be too weak, or because the sensor will detect movements of muscular areas that are not of interest to us, or because the measurements will be noisy. In the context of our project, the physical activities to be determined are standing, sitting, walking and running (and possibly others).

Also, an important constraint to take into consideration: we must use only one sensor. Where others use several to capture the variations of several areas, we must identify the best one in order to optimize the signal that will be processed. Many of the reports I have reviewed compare multiple sensor positions, generally the areas typically tested are the wrist, ankle, torso, and hip. With the exception of [1], where two sensors are placed above and below the knee because the study was oriented around activities eliciting knee flexion specifically. Also, in study [10], the sensor is placed at the lower back, at the L5 vertebra. But again, the main purpose of this study was to determine the number of steps taken around a predefined pathway, and to compare these results to those obtained in a controlled laboratory environment. Moreover, here only walking was studied.

Another very important point is to make sure that the sensor is well secured and that it is well placed on the person so that it does not move freely. There is a risk of capturing parasitic movements that would distort our measurements.

Concerning the position of the sensors, according to [11], positioning the sensor on the wrist does not allow us to obtain satisfactory results compared to when the sensor is placed on the torso: there is too little variation between walking and running. The study [7] obtains better results (86%) when the sensor is positioned on the ankle.

The study [15] makes an interesting comparison between single sensor systems and those including several sensors. The best result is obtained with 4 different sensors, each one placed on the torso, waist, thigh and ribs. But the best single sensor configuration is the one where the sensor is placed on the waist (>90% accuracy).

With all this information, it would be wise to move towards a sensor positioning at the ankle or waist. This remains to be verified experimentally with our equipment.

# Software Study

## Data pre-processing

Before being able to use the algorithms, it is imperative to have a usable signal in order to extract the necessary information. Some studies, such as [1], have used a low-pass filtering stage with a fc of 15Hz. The research [2] uses a low-pass filter for the data from the gyroscope and the accelerometer, then the filtered data from the gyroscope undergoes a high-pass filtering stage at a cutoff frequency of 0.005Hz, in order to avoid the gravitational acceleration generated.

## Processing methods

In the majority of research papers, the data is acquired from the sensor (IMU or accelerometer alone), then processed (and possibly conditioned and qualified) on the acquisition apperatus, before being transmitted to the PC. The different algorithms are then executed with the data acquired with the device on a PC. Unfortunately here, what we are trying to achieve would be, ideally and if possible, to implement the algorithm part directly on the ESP32. Even if there are libraries such as *TensorFlow Lite* allowing to implement artificial intelligence on the ESP32, this one will also have to have the capacity to do the data acquisition, the preprocessing, the qualification and consequently the algorithm part with Machine Learning.

The study [4] implements *TensorFlow* in an ESP32, but in this case it is not about recognizing different activities, but only about determining if the individual has fallen to the ground, which implies much less complexity than our project. I don't know if the module will be able to handle all this workload. If not, I could follow the papers [2] and [11], where only the acquisition and preprocessing phase (eventually) is done on the embedded module, the data is then sent to the PC to be analyzed and to display the data in real time.

There are several methods used to categorize the acquired data: the first one consists in experimentally establishing basic thresholds; if the measured data exceeds a certain threshold, as in [11], the decision is only oriented according to whether we are above or below the fixed value. This method does not require artificial intelligence, is relatively simple to implement in the embedded system, but is not appropriate in our case: our goal is to identify several physical activities. Here, the goal of the study is to know if the individual has suffered a fall or not. One (or more) simple thresholds will not be sufficient here.

The second method is to use more complex Machine Learning algorithms. Machine Learning can be defined as an artificial intelligence technology that allows machines to learn without having been specifically programmed to do so. Machine Learning is explicitly linked to Big Data, since in order to learn and grow, computers need data streams to analyze and train on.

There are two main categories of algorithms: supervised and unsupervised learning. Unlike supervised learning, unsupervised learning uses unlabeled data. From this data, it discovers patterns that help solve clustering or association problems. Some examples of supervised algorithms: Artificial Neural Networks (ANN), Naive Bayes, Linear Regression, Support Vector Machine (SVM), Randon Forest and K-Nearest Neighbors (kNN) among others. Unlike the main unsupervised algorithms such as Clustering K-means and Gaussian Mixed Models (GMM) or Hidden Markov Model (HMM) for example, supervised algorithms are simpler and require less computing power, while being more reliable. However, the time required to train the algorithm can be relatively long.

The first step is to establish, using complex mathematical tools as shown in [14], a pattern for each activity from a data set. Here, the signals are first normalized, then one of the signals is chosen and an inter-correlation between this data and the others is performed. This results in several patterns, which are similar but still have differences; the way we walk between each acquisition is ever so slightly different each time. We then perform an averaging between all these patterns in order to obtain the pattern that will identify the data. This is an example among many other possibilities, it depends on many variables (sensor used, parameters, calculation methods, what type of activity we want to identify).

Once we have a pattern that best represents the desired physical activity, we can then train a Machine Learning algorithm for example. There are many different algorithms, including Artificial Neural Networks (ANN), k-nearest neighbor (kNN), decision trees, Random Forest. The majority of studies have trained the acquired data on several algorithms in order to determine the most suitable for the situation such as [4], [13] and [14]. In this case, after analyzing the different research papers, it seems complicated to draw a clear conclusion about the best algorithm to use. The study [4] obtains a maximum accuracy for the kNN method, [13] with Naive Bayes, and [14] with an ANN. This gives me some clues as to which algorithms to use, but the solution is not so obvious.

# Conclusion

The analysis of this small selection of scientific journals and research papers allowed me to learn more about the methodology used to determine the best solution to a given problem. I now have a clearer vision of what to expect from the project.

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