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Towards an Integrated Solution to Physical Assessment of Students

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Resumo

No presente trabalho é proposta uma solução de suporte ao sistema de avaliação de alunos no âmbito das aulas de educação física. Foram recolhidos dados de acelerometria de alunos durante a execução de diversas atividades, através da utilização de um smartphone e de uma aplicação móvel desenvolvida para o mesmo. Os dados de acelerometria recolhidos são usados para extração de informações relacionadas com atividade física, tais como gastos energéticos, número de passos e intensidade da atividade. Estes dados encontram-se disponíveis numa aplicação web desenvolvida, que apresenta os gráficos de atividade e informações relativas ao aluno. O objetivo principal deste estudo é o desenvolvimento de uma solução para complementar o processo de avaliação no contexto de aula de educação física, fornecendo informações relativas à atividade física do aluno. Esta informação estará sumariada e prontamente disponível de forma a ajudar e complementar o processo de avaliação do professor. Ao envolver também os alunos neste processo, espera-se que estes apresentem uma maior motivação para a prática de um estilo de vida mais ativo, fornecendo-lhes informações visuais sobre a sua atividade, o que lhes permitirá comparar resultados entre eles e, possivelmente mais importante, avaliarem a sua própria evolução.

Os dados de acelerometria são disponibilizados de forma gratuita à comunidade, assim como a aplicação móvel para recolha de dados de acelerometria, juntamente com o seu código fonte.
As experiências efetuadas forneceram a prova de conceito necessária para promover esta solução como um valioso aliado no processo de avaliação em aula. Além disso, estas experiências foram essenciais para verificar o valor prático da métrica de avaliação proposta num ambiente de aula de educação física tecnologicamente heterogéneo.
Como efeito deste trabalho, um grande conjunto de informação relativa à atividade física do aluno do foi produzido. Este conjunto de dados apresenta algum desafio relativamente à identificação de atividades e é disponibilizada de forma gratuita à comunidade de aprendizagem automática.

Palavras Chave

Métrica de avaliação física, acelerometria, estimativa de gastos energéticos, sistema de suporte à avaliação, reconhecimento de atividade, motivação do estudante, biblioteca de dados de acelerometria.

Abstract

In this work, we propose a solution to support the student’s assessment process in physical education classes. Student’s accelerometry data performing several activities was collected using a smartphone and a developed mobile client. The collected accelerometry data is used for activity information extraction such as energy expenditure, number of steps and activity intensity. This information is displayed in a developed web application along with charts and student information.

The main goal of this work is to develop a solution to complement the physical education class assessment process, by providing student’s activity information extracted from accelerometry data. This information is summarized and made readily available as a mean to aid and complement the teacher’s assessment process and grading system. By involving the students in the new class assessment system we also hope to motivate them to practice a more active lifestyle, providing them with visual information about their activity and allowing them to compare statistics between each other and, perhaps more important, evaluate their own evolution.

The collected accelerometry dataset is made public to the community, as well as a free and open source mobile client for data collection.

The performed experiments provided the necessary proof of concept to promote this solution as a valuable ally in the student assessment process in class. Moreover, these were essential to verify the actual practical value of the proposed assessment metric in a technologically heterogeneous physical education class environment.

As a side effect a great set of information regarding student’s activity was produced. This dataset poses some hard challenges regarding activity identification and is made freely available to the machine learning community.

Keywords

Physical assessment metric, accelerometry, energy expenditure estimation, grading support system, activity recognition, student motivation, accelerometry dataset.

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Acronyms

API	Application programming interface
BMI	Body mass index
BRM	Base metabolic rate
DLW	Doubly labeled water
EE	Energy expenditure
EEact	Energy expenditure in activity
GPS	Global positioning system
Kcal	Kilocalorie
KNN	K-nearest neighbor
MET	Metabolic equivalent of task
MLP	Multilayer perceptron
REE	Resting energy expenditure
SD	Secure digital
SDK	Software development kit
SVM	Support vector machine
TEE	Total energy expenditure
VO2	Maximal oxygen consumption

1. Introduction

1.1. Motivation

Over the last few years, excess weight has increased at alarming rates worldwide. Recent studies show that between 1980 and 2013, the proportion of adults worldwide with excess weight has increased from 28.8% to 36.9% for men, and from 29.8% to 38.0% for women [1]. Obesity is a cause of millions of deaths worldwide, also reducing life expectancy and causing other kinds of disabilities [1].

Children are also being affected, as of 2013, 23.8% of boys and 22.6% of girls being overweight or obese [1], having a greater likelihood of cardio-metabolic risk factors and remaining obese as an adult [2], with a chance of being obese as an adult exceeding 50% after six years of age [2]. This alerts to the need of a proper close monitoring of children of young age, guiding them throughout the years, motivating healthy and active lifestyles. Recent studies also suggest that certain behaviours in children, like a low level of moderate to vigorous physical activity, short sleep duration and high level of sedentary activities like TV viewing are some of the most important correlators for child obesity [3] and major diseases prevalence [4].

New technology has been introduced in schools, with interactive whiteboards, computers and video projectors present in many classrooms. Although mobile phones in general are still prohibited by schools, smartphones brought new functionalities that may be useful in the classroom environment, such as note taking and calculations. With the development of new applications that take advantage of these devices, they might prove a useful and effective education tool.

Children are already being taught to some extent, the practice of physical activity in school through classes dedicated to it. The same methods of teaching and evaluation have been used for the last several years, making them somewhat outdated by not making use of some of the innovative technologies available today, ultimately making students lose interest in the lectures and disregard the importance of physical activity.

Smartphone usage has grown dramatically over the last few years, with over 2 Billion smartphones worldwide [5], [6]. Children nowadays are being raised surrounded by technology, with a big and increasing number owning a smartphone. These smartphones contain key features such as multiple sensors, providing external data information such as magnetic field (magnetometers), temperature, orientation (gyroscopes), atmospheric pressure (barometer), global positioning (GPS) and acceleration (accelerometers).

The student assessment in physical education classes presents several challenges mostly resulting from the heterogeneous environment with high variability on aspects such as availability of different sensors, different demographic groups, different physical backgrounds and different activities performed. This makes the results hard to compare, resulting in a student evaluation process permeated by some subjectivity, generating the need for a clear and unbiased way (at least to a greater extent) to perform the grading of the students.

The quantification of Energy expenditure (EE) has gained interest over the last years, with several methods, devices and applications being developed such as the reliable measurements provided by doubly labeled water (DLW), indirect calorimeter, estimations based on accelerometry data and heart-rate values and applications that make use of these estimations like fitness trackers and other smartphone apps [7–12].

Building solutions targeting smartphones’ sensors and children is a viable idea, since this demographic group is enthusiastic about technology, specially about mobile applications.

1.2. Objectives and synthesis of the state of the art

Activity recognition is an area of extended research, with applications in health monitoring, sports, entertainment and other areas. With the advent of smartphones, several studies have been conducted regarding activity recognition using multiple sensor data collected from smartphones [13–16], whereas previous studies, e.g. the work presented in [9], relied on sensor data provided by dedicated devices like the *actigraph gt3x+* and the *TriTrac-R3D*. By using a smartphone for sensor data collection, the cost of this type of system is greatly reduced, since we only require an application to record raw sensor data, and a means of transportation for the device.

In Akram Bayat et al.[15], a model was developed that is able to recognize multiple daily activities using machine learning, such as aerobic dancing, using a single Android smartphone with an accelerometer sensor, placed on the hand, or in the pocket. They concluded that combining classifiers and using the average of probabilities through the fusion method resulted in an overall accuracy of 91.15%.

In Armir Bujari et al. [17], other types of pattern recognition are studied such as day-by-day street behaviour, like crossing a street. This kind of behaviour detection can be used to automatically build a database of cross lights, by making use of the great number of smartphone users. By using an iPod Touch 2G with a tri-axial accelerometer. The accuracy of detecting the mentioned behaviour was of about 80%. Pedestrians need to follow strict rules such as accelerate their pace when crossing.

In Edmond Mitchell et al [13], different sports’ activities were recognized using machine learning, like hitting the ball, tackling and sprinting, from a collected dataset comprised of soccer and field-hockey activities. A total of 32 subjects participated in this study. The sports matches were also recorded in order to match accelerometer data with video data. Their maximum accuracy was 87% using a fusion of classifiers.

There are other studies combining multiple sensors in order to try to increase the accuracy of the activity classification. In A. Pande et al [10], a smartphone’s accelerometer and barometer sensor was used to estimate EE using machine learning. These trials obtained a superior EE estimate compared to expensive consumer state-of-the-art devices like *Fitbit, jawbone* and

Nike+ FuelBand. A smartphone's barometer sensor was used to improve EE estimation accuracy, by providing data about the environment's atmospheric pressure and proving to significantly increase the accuracy of EE estimation, especially on altitude change activities such as climbing stairs.

In Wanmin et al [16], an accelerometer sensor was combined with a gyroscope sensor, both present in an iPod touch, in order to obtain the gyroscope sensor effectiveness in activity classification. Using machine learning and combining the orientation data with accelerometry data, they concluded that using gyroscope sensor readings proved to be beneficial.

Calorimetry equations provide a fast way of estimating EE from the subject's physical information and accelerometer counts. Two popular equations were developed by K. Y. Chen et al [9], using a *Tritrac-R3D* for data collection. A linear relationship exists between accelerometer counts and EE and some physical activities, allowing the estimation of EE during physical activity (EEact).

Using a common device like a smartphone and making use of the acceleration sensor available in it, we aim to create a solution that aims to improve the current assessment system used in physical education classes, by providing information about the student's daily physical activity, including energy expenditure, number of steps and several charts regarding physical activity. This solution will also provide support for multiple day analysis, as a way of comparing the student's physical evolution, including body mass index (BMI) and weight.

The option for using solely accelerometry data is motivated by the current presence of accelerometers in almost every smartphone available. The usage of other sensors would also increase system storage requirement and reduce battery life on the mobile client [10].

In this work, the proposed solution requires a mobile client, in this case deployed as an Android mobile application, that collects accelerometry data and uploads it to a server through a wireless connection, where the data is processed, extracting several types of information. The server contains an analysis tool that extracts information, and generates various activity graphs. The server also hosts the frontend web application to access all the extracted information and generated graphs.

We aim to implement a data collection protocol in a school, with students collecting accelerometry data with their smartphones during physical education lectures, performing a list of pre-defined activities. The smartphone will be transported in a waist bag provided to them and the students will follow the teacher's instructions. This data will then be processed and the synthesized information will be readily available to assist and complement the teacher's evaluation process.

This prototype will help to estimate the effectiveness of accelerometry data in the context of a class assessment tool, computing the energy expenditure and other measures that may help to evaluate the student.

The developed Android mobile client for data collection and its source code, as well as the collected accelerometry datasets will be made public, with the goal of helping to develop new application that promote active lifestyles thus improving the quality of life.

1.3. Main contributions

The main contributions in the developed work are as follows.

We propose and developed a solution to complement the assessment process in Physical educations classes, using the student's smartphones to collect accelerometry data, and extracting activity information to complement the teacher's assessment and grading system. We hope to motivate children to practice a more active lifestyle and improve children's effort in class, by providing them their activity results and allowing them to compare those results between each other. With this we hope to fight obesity and other diseases by helping to create good habits in children in school age.

An accelerometry dataset library was collected, composed of a collection of activities performed in a physical education class environment and it is made available to the community.

A mobile client for the Android OS was developed to collect accelerometry data, and automatically upload it to our server along with user information. This is made available in the play store [18] along with its source code [19].

A new metric using accelerometry values collected by different heterogeneous devices was proposed consisting in the accelerometry data reduction. The preliminary results are encouraging regarding the possibility to deliver a more accurate and reliable activity comparison between subjects.

A linear EE equation [9] was implemented and adapted to use raw accelerometry values, estimating EE with good accuracy for linear activities, providing a simple and easy to implement method of calorie estimation.

1.4. Organization of this document

This paper is organized as follows. In Section 2, a brief overview is made regarding related works in the area of accelerometry, activity recognition and energy expenditure. The literature studied will serve as the basis for this work, specifically in energy expenditure calculation and activity recognition. Section 3 proposes a new metric for accelerometry data reduction, allowing a more reliable comparison between student's statistics, presenting results using this metric applied to the collected school accelerometry datasets. Section 4 describes in detail the work developed applying important knowledge extracted from the literature. Diagrams are presented to provide an overview of the work developed followed by a detailed description of the development process of the mobile client, frontend web application, the server configuration and the activity assessment tools. Section 5 discusses the methodology of the prototype implementation and the dataset collection process. We discuss how the data collection was prepared and performed, equipment used, and the population characterization.

Section 6 includes the results of the energy expenditure estimation and activity recognition experiments, testing different datasets with multiple classifiers and data pre-processing techniques based on the studied literature. Section 7 provides a summary and main conclusion of all the developed work, as well as future functionalities and features to implement. Section 8 provides concluding remarks, discussing all the work and the biggest challenges.

2. State of the Art

2.1. Introduction

In this chapter we discuss the current state of the art for different areas related to this work. First we will discuss accelerometry: what it is, how it works and areas of application. We will see how an accelerometer is such a simple and technologically advanced device, and how we can replace expensive tools and frustrating processes with it. This will allow us to move to the next topics, describing some of the accelerometry applications in detail, the state of the art for those application areas and how we combine them in this work.

2.2. Accelerometry

A modern accelerometer is a microelectromechanical systems (MEMS) device. In other words, it is a very small device with components between 1 to 100 micrometres that contain moving parts (Figure 1). Conceptually, the moving parts of an accelerometer are composed of a mass on a spring that reacts to acceleration. When this mass is displaced by acceleration, the spring is able to accelerate the mass at the same rate as the casing, and this displacement is measured as acceleration.
Modern MEMS accelerometers are integrated in smartphones, and are simple devices consisting of a rigid arm structure with a proof mass and a casing. This allows them to be of very small size and have a very low production price.

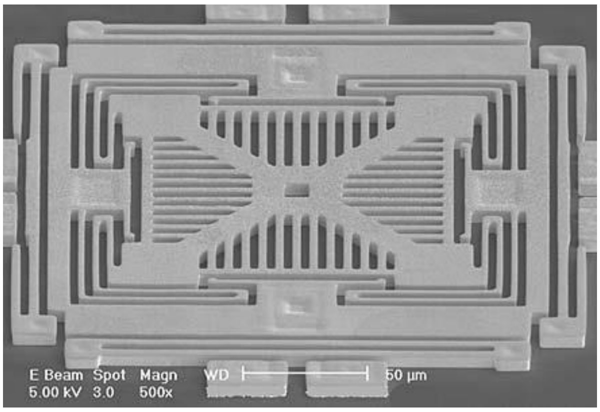

Figure 1 – Example of the micromechanical structure of a 3-axis MEMS accelerometer [20].

These MEMS devices enabled the integration of several sensors inside small and common devices, like smartphones, thanks to their small size and very low price. This enabled a whole new generation of applications for different areas, like medical and health [21-22], sports [23], [24], entertainment [25–28], engineering [29], biology [30–32], industry [33], building and structures [34], navigation [35] and others.

With the advent of the smartphone, several accelerometry uses have been studied and applied on different areas. One of the most common uses is the is the pervasive task of detecting device positioning for screen rotation. There are other kinds of innovative applications like fall detection for elderly , image stabilization [36], orientation sensing, device integrity [37], and motion input [38].

A 3-axial accelerometer returns linear acceleration values providing simultaneous measurements in three orthogonal directions (axes X, Y and Z). These values of acceleration contain the element of gravity, which always returns 9.81 m/s^2. So an accelerometer that lays flat on a surface will report the acceleration of gravity on the vertical axis. This value can be omitted so that only the acceleration of the body is accounted for.

2.3. Energy expenditure estimation

The determination of the energy expenditure for a human body provides important information regarding its level of physical activity and helps to prevent chronic diseases such as obesity and diabetes (by controlling calorie intake).

Energy expenditure (EE) can be accurately measured using technics such as doubly labeled water (DLW) for activities of long duration, direct calorimetry which requires observations in a confined metabolic chamber, and indirect calorimeter such as the portable Cosmed K4b, suitable for short to medium periods of activity due to its size and required face mask. These devices and techniques are expensive and are currently the state of the art for EE measurement. There are some other alternative methods for EE prediction that are currently being researched. These don’t guarantee as much accuracy, but offer other benefits such as lower price and portability, either by using accelerometer reading devices such as the *actigraph gt3x+*, the *TriTrac-R3D* [9] or more recently by using a smartphone’s built-in sensors [10]. Other devices include heart-rate monitors or pedometers [39].

This kind of data has limitations, as it cannot detect subtle changes in EE or the thermic effect of food, making it better suited for short to medium duration specific activities.

In K. Y. Chen et al [9], two popular equations for energy expenditure estimation in activity (EEact) were proposed. A number of 125 subjects (53 men and 72 women) were studied for 2 days. On the first day, the subjects performed a normal daily routine, and in the second day a set of defined exercises to measure minute-by-minute acceleration. All activities were recorded using the *TriTrac-R3D* placed on the right hip and for accurate values a whole-room indirect calorimeter was used.

Two models were developed, a linear and non-linear model. The EEact calculated by the linear model was lower than the measurement by the calorimeter, specifically on light-intensity activities, contributing to an underestimation of total energy expenditure (TEE). The non-linear model improved EEact calculation on both light-intensity daily activities and on exercise day activities, improving the standard errors of estimation.

In their models, the X and Y axes are combined as the horizontal value *H* (1),while the Z axis was isolated as the vertical value *V*, as it differs from the other two vectors because of the gravity applied.

$$H = \sqrt{(X^2 + Y^2)} \quad (1)$$

The linear model obtained (2), estimates EEact with the input a_L(3) and b_L (4) representing the regression parameters.

$$EEact(k) = a_L * H(k) + b_L * V(k) \quad (2)$$

$$a_L = \frac{[5.78 * mass(kg) + 11.95 * height(cm) + 6.89 * age(yr) - 2{,}001]}{1{,}000} \quad (3)$$

$$b_L = \frac{[5.69 * mass(kg) + 349.5]}{1{,}000} \quad (4)$$

In the non-linear model (5), *V* and *H* were applied with two power parameters for the modelling of the nonlinear relationship between EEact and body acceleration. The input a_N and b_N (6(7), represent the regression parameters. Both equations represent EEact for the *k*th minute in kJ/min.

$$EEact(k) = a_N * H(k)^{P^1} + b_N * V(k)^{P^2} \quad (5)$$

$$a_N = \frac{[12.81 * mass(kg) + 843.22]}{1{,}000} \quad (6)$$

$$b_N = \frac{[38.90 * mass(kg) - 682.44 * gender + 692.50]}{1{,}000} \quad (7)$$

The regression parameters were derived from the subjects, and generalized to a given body mass, height and age using linear regression analysis. These parameters contribute to the estimation of EEact, as different people with different age, height and weight will generate different resulting values. The power parameters *p1* and *p2, are given* respectively by Equation 8 and 9.

$$p1 = \frac{[2.66 * mass(kg) + 146.72]}{1{,}000} \quad (8)$$

$$p2 = \frac{[-3.85 * mass(kg) + 968.28]}{1{,}000} \quad (9)$$

After all accelerometry data was collected, EEact predicted by the linear and non-linear equations were added to the resting energy expenditure (REE) to derive total EE. The values were then compared to those measured by the indirect calorimeter, obtaining the difference and measuring the obtained accuracy.

In A. Pande et al [10], a smartphone's accelerometer and barometer data was used to estimate EE in a group of 12 subjects. The data was collected using different smartphones, in a variety of exercises such as walking, climbing stairs and standing still. Their focus was to define a single robust EE algorithm that can be applied to all activities. The selection of features is very important in machine learning, as we need to identify features with high correlation to EE. The use of accelerometer raw values against feature vectors was compared, observing a clear advantage of using extracted features. A low sample rate of 2Hz (2 samples per second) was used based on Bouten et al [11], which shows that a sampling rate of 0.1-20Hz is a sufficient range. The window size is also important to identify activities, and was defined at 4 seconds (8 samples) for this study. A total of 28000 samples were obtained. Using machine learning and a combination of feature vectors (gender, age, height, weight, BMI, mean of accelerometer vectors and barometer signal) they were able to estimate EE from smartphone sensor data, with an 96% correlation with actual EE. The linear calorimetry equation value (2) was also used as a feature vector, although after some tests it was removed, having no impact on EE prediction using machine-learning approaches. The collected EE values were calibrated against a COSMED K4b2, which uses pulmonary gas exchange to measure caloric expenditure with great accuracy. These trials obtained a superior EE estimate compared to expensive consumer state-of-the-art devices like Fitbit and the Nike+ FuelBand. A smartphone's barometer sensor was used to improve EE estimation accuracy, by providing data about the smartphone's elevation and proving to significantly increase the accuracy of EE estimation, especially on altitude change activities such as climbing stairs. In this study, an interesting analysis of the battery consumption of the accelerometer, barometer and gyroscope sensor is made, with the gyroscope generating a very big power consumption compared to the other sensors. The sampling rate and power consumption was also compared, showing a much bigger draw using high sampling rates (100Hz) than low sampling rates (2-50Hz). These should all be taken into account before implementing such solutions, especially if performing data collections for long periods.

2.4. Human Activity Recognition Using Accelerometer

Activity recognition is one of the most studied areas of accelerometry use. Typically, by using machine learning (a combination of classifiers) and accelerometry data, we can identify with great accuracy a large set of activities. Nevertheless, this method of classification has some limitations, given that a 3-axial accelerometer alone is not enough to correctly identify some activities of low intensity, of changing altitude, or activities where the device is placed in a stationary position, like cycling or elliptical.

Activity recognition is useful in many areas, allowing for example a doctor to evaluate a rehabilitation patient by distance, reading and analyzing the movement's execution with great precision. The same can be applied in sports, where a perfect technique can be evaluated, identified, and used in other player's technique evaluation and correction. It can also be useful for EE estimation, as knowing the activity being executed can deliver a better estimate.

In Akram Bayat et al.[15], a model was developed that is able to recognize multiple daily activities such as slow and fast walking, aerobic dancing and going up and down stairs, using a single Android smartphone placed on the hand or in the pocket. Their goal is to identify new activities using less sensory work than previous studies. These activities were executed in sequence, pausing a few seconds between activities in order to correctly identify them. Data was captured at 100Hz, and 180 to 280 seconds of data were captured, resulting in a total of 79,573 samples. They designed a low pass-filter in order remove gravity information from the datasets. Features were extracted using window overlapping, taking advantage of periodic behaviours with distinct patterns to calculate those features. Using a window of 128 samples (1.28 seconds of data) and 50% overlap, since this number of samples is enough to identify cycles in the executed activities, they extracted features such as mean for each window elapsed time between consecutive peaks, the difference between the minimum and maximum for each window and the correlation between different axes. In total, 24 features were extracted, but only the 18 best were used. Several classifiers were trained with the 4 subjects using a 10-fold cross validation method on the set of extracted features. For individual classifiers, Multilayer Perceptron offered the highest performance, with 89.48% accuracy for in-hand smartphone, and 89.72% for in-pocket, showing a negligible difference, although in-hand smartphone is not practical, since the subjects can't rotate the smartphone or change its position. Combining the best single instance classifiers and using the average of probabilities through the fusion method resulted in an overall accuracy of 91.15% for in-pocket and 90.34% for in-hand. The best classifiers combined were Multilayer perceptron, SVM and Random Forest. Overall, maintaining the smartphone in a fixed position helps with classification.

Other types of activity recognition can be studied such as day-by-day street behaviour, like crossing a street. In Armir Bujari et al. [17], it is proposed the construction of a database of crossroads and traffic lights for use in google maps. This database would automatically be generated by a multitude of user's smartphones sensors, automatically detecting when the user crosses the street and sending the GPS coordinate to a server. This study was done by using an iPod Touch 2G with a tri-axial accelerometer, the data was collected at a 30Hz rate and applied to a high-pass filter, in order to collect higher values. The only feature vector used was the magnitude of the three axes. The accuracy of detecting the mentioned behaviour was of about 80%, as the pedestrians need to follow strict rules, such as accelerating their pace when crossing, generating some false-positives.

In Edmond Mitchell et al [13], using various extracted features, window lengths and multiple classifiers, different activities were recognized for two different sports. The data was collected at a rate of 16 to 22Hz. The activities identified include hitting the ball, tackling and sprinting. The smartphone was placed on the upper back, recording one hour of data for each sport. The two sports included in this study were soccer, with 15 players and field hockey with 17 players. The sports matches were also recorded in order to match accelerometer data with video data. For optimum results, the window size was adjusted between sports due to the difference in the activity duration. The classifiers used were SVM, KNN, Naive Bayes, J48 and Artificial Neural Networks. Four datasets with 210 activities were created, with two thirds used as training data, and the remaining as test data. In experiment 1, with a window size of 5 seconds and using an SVM classifier, achieving a 65.9% accuracy for hockey and 62.7% for soccer. This approach was the fastest to train and create, but obtained poor performance. In experiment 2, a full range of classifiers were tested. All performed similarly except SVM during soccer activities which performed badly (54%). Window length changes affect the output of the classifiers. If two or more activities occur in a window, then classification difficulty is increased. When selecting a time window it must be long enough to contain the entire activity being performed and short enough that it does not include any additional ones. The best classifiers in this experiment were Naive Bayes for the soccer activities and MLP for hockey. Experiment 3 used a fusion of classifiers by creating a separate model for each activity. This approach obtained a 6% better accuracy than the best single classifier, however with a significant increase in computation costs. Game activities like tackling and hitting the ball were harder to identify due to similar motions performed. Reference methods in Kwapisz et al [12] were tested, since they reported an accuracy over 90%, but only achieved an average accuracy of 73% for soccer, and 79% for hockey, demonstrating that it is difficult to develop a generalized approach for activity recognition, each dataset requiring its own window size, feature set extraction and testing with different classifiers.

In Wanmin et al [16], a gyroscope sensor present in an iPod touch was used, combined with accelerometer readings from the same device. A group of 16 subjects participated, executing a total of 13 activities, ranging from everyday activities and treadmill walking at different speeds. The device was carried in the pocket and data was collected at a sample rate of 30Hz. Different window sizes were tested (1, 2, 5 and 10 seconds), obtaining the best classification accuracy using a 2 second window size, containing about 60 samples. The feature set was composed of the mean for each axis, the standard deviation, the sum, and the fast Fourier transform magnitude. The classification process used several classifiers: J48, multilayer perceptron, naive Bayes, logistic regression, and KNN, always with default settings and 10-fold cross-validation. KNN obtained the overall best accuracy, with 90.1-94.1% for walking at different speeds, 100% for sittings and 91.7% for jogging. Stair walking proved to be a challenge for all classifiers with accuracies ranging from 52.4 to 79.4%. Removing the gyroscope sensor values resulted in a decrease in accuracy, with a decline from 3.1% to 13.4%, with KNN still producing the best results. Gyroscope is proven useful since most activities have an orientation change, complementing accelerometer values in activity recognition. These precision gains may be negligible in other studies, so gyroscope usage should be studied a priori, since it is a sensor with high power consumption [10].

2.5. Related works and applications

Accelerometers provide the means of converting an external input to digital information. In this case, acceleration over the accelerometer body is translated to a force value on the affected axis. This capacity of reading external acceleration forces is very useful, and has application in numerous areas.

In engineering, accelerometers can measure vibration of vehicles and buildings, including inclination and speed, allowing the development of new safety systems that can measure the viability of structures [34]. A laptop for example, can include an accelerometer to implement hard-drive protection on fall [37]. Earthquake detection is also possible using a network of devices equipped with vibration detection [40]. A common use of accelerometers in the automotive industry is airbag deployment, detecting rapid negative deceleration of the body to identify a collision [41].

In Biology, accelerometers allow the quantification of animal movement and energy expenditure in the wild, making use of accelerometry data and energy expenditure estimation [30].

An accelerometer can also be used to calculate the number of steps, leading to applications that stimulate the users to practice physical activity like Google Fit [42] or Pedometer & Weight Loss Coach [43]. Sleep monitor is also possible, with application such as Sleep as Android [44] detecting sleep patterns and waking the user at the best time. These features can be implemented in software, taking advantage of smartphone sensors, or through dedicated devices like fitness bands, such as the Fitbit [45], Mi-Band [46] or Jawbone [47]. These small devices have an integrated accelerometer, allowing the integration of the previously mentioned functionalities.

Measuring strike force is also possible in a variety of sports, as well as any type of collision between players and the player's technique, demonstrating that sports is an excellent area to apply this technology [23][48].

In industry, condition monitoring is an important aspect, since it can lead to high expenses in equipment failure [33]. Accelerometers can detect equipment faults through vibration before failure, avoiding downtime and costly repairs. These systems are currently used in industries such as automotive, power generation and pharmaceutical [33].

In navigation, accelerometers can be used to help obtain the position, orientation and velocity without the need of an external reference [35]. Although in these kind of systems, a gyroscope is commonly used to assist navigation since accelerometer measures linear acceleration but only relative to the moving system, and are not aware of their own orientation.

Another common area of accelerometer use is entertainment, with devices such as the Oculus Rift [26], HTC Vive [25], Samsung Gear [28] or Google cardboard [27] providing real-time head tracking for immersive experience. Oculus Rift and HTC Vive both have integrated accelerometers, while Samsung gear and Google cardboard rely on the smartphone's sensors. Rotating a device's screen automatically is made possible by the use of an accelerometer, by detecting the force of gravity in the correct axis.

Image stabilization can also be achieved through the use of accelerometers, canceling out unintended motion. This is commonly used in smartphones, taking advantage of the sensors available to overcome hardware size limitations of smartphone camera sensors [36].

2.6. Remarks

Accelerometers have been a powerful ally in developing new and innovative applications in many different areas. The miniaturization of this sensor allowed new kinds of interaction and movement reading as a result of the precision available these devices. Judging by the extensive research done on many areas, like medicine, industry, biology, engineering and navigation the possibilities are manyfold. This kind of research aims to improve quality of life and quality of service, by replacing old, occasionally time-consuming and expensive solutions.

The analyzed literature provided valuable insights regarding energy expenditure estimation. The equations developed in [9] provide a fast and reliable means of EEact estimation. Machine learning techniques provided a better EE estimation than calorimetry equations [10], although they require dataset building for all activities to estimate, as well as reference values collected through reliable methods like pulmonary gas exchange. These equations might underestimate or overestimate EEact for different people and different activities, but provide a good ab initio approach to work with, using only raw accelerometer data and the person's body statistics like height, weight, age, and sex.

The literature review was also very useful for activity recognition, presenting several good methods for data pre-processing and feature extraction.

3. Proposal of a Metric for Physical Education Class Assessment

3.1. Introduction

Comparing the physical activity and the effort applied in class between different students is one of the objectives of the proposed solution. Due to heterogeneity in our subject group, like physical capacity, weight, height and gender, direct comparison between subjects using extracted information like the accelerometry magnitude, may not provide a reliable means of comparison. The heterogeneity of the devices used for accelerometry collection, also presented a challenge for direct student comparison, since these devices may have different sampling rates and accelerometers with different sensibility and precision. Without a means of removing the biases related to these factors, student comparison is not reliable, allowing only the evaluation of student activity evolution regarding their own collected data.

Developing a reliable means of student activity comparison, using different physical characteristics and different accelerometry values is important, and will allow the teacher to compare activity statistics between different students for a better assessment and student monitoring throughout the school year.

3.2. Comparison between students

In the assessment solution here proposed, student activity evaluation over-time can be performed by analyzing multiple extracted features such as the magnitude of each axis, the mean of the total magnitude, the number of steps and the energy expenditure estimation (EE). These measurements deliver information that can be used in student evolution assessment, but are not optimal for comparing statistics between students since they might have different physical characteristics, and their accelerometry data might have been collected by different kinds of devices.

To compare multiple subjects, it is necessary to develop a common measurement between students that is independent of the used device for accelerometry data collection and student's physical characteristics. This measurement must previously perform a calibration between all students, in order to eliminate the differences between different devices.

A common mean of activity intensity measurement, that can be used to compare multiple subjects of different weight is the metabolic equivalent of task (MET). This measurement expresses the intensity of physical activity, with one MET being represented as the energy expenditure at rest (REE) or the quantity of oxygen consumed by the body (VO2) at rest [49]. The energy cost of a physical activity is calculated as the MET value multiplied by the REE value. This resting energy expenditure value can be obtained through accurate measurement tools like doubly labeled water (DLW), indirect calorimeter, or estimated by using the subject's information like height, age, sex or weight. A value of 2 MET's means the subject is expending 2 times his resting energy expenditure, a value of 3 MET's requires three times the resting energy expenditure, and so on. MET can be thought of as an index of the intensity of activities (see Table 1), in a way comparable among people of different weight [49].

The MET value is commonly used as a measurement of activity intensity, since using energy expenditure alone doesn't allow comparison between subjects of different weight being their relative energy expenditure different for the same activities. To estimate the base MET value for a subject, his REE must be estimated by a reliable method, or by doing an estimation using the subject's body weight (see (15) in section 6.2).

Table 1. Standard MET guidelines for some activities [50]

Activity	**MET value**
Resting	1
Personal Care, Household activities	2
Cooking, shopping, housework, casual games	3
Playing soccer	7
Martial arts, rugby	10

3.3. Accelerometry data reduction

Student activity comparison is not reliable using directly extracted features such as the magnitude or number of steps, since the devices used for accelerometry capture are different, and subjects have different physical characteristics (see Table 14).

Departing from the previously analyzed MET measure, which aims to the direct activity comparison between subjects of different weight, we propose the following method of data reduction, arguably allowing student comparison in a more reliable way.

In MET estimation, a base REE or VO2 value for 1 MET is needed to estimate other activities. In this proposed metric, the mean of the magnitude for a short period and high intensity activity is extracted independently for each student, defining our base measurement. The activity used for this measurement is running, since it provides consistent accelerometry values. In the following we will refer to this metric as the running equivalent of activity (REA). This base measurement will allow to uniquely sample each student's physical capacity in relation to the reported accelerometry magnitude values, allowing to perform a calibration and estimate other activities by dividing the activity magnitude by the base value of 1 REA.

Students collect accelerometry data while running for a short period of time at high intensity. After this data is collected, the average magnitude for that activity period is calculated, providing the base magnitude value for a normalized REA value of 1. Gravity is also removed using a low pass filter [51], in order to extract only the acceleration of the subject, otherwise a vertical acceleration force would be incorrectly reported when students are standing still. It is important that students perform the running activity at their maximum intensity without interruptions since all the subsequent activity estimations will depend on this ground truth data.

The computed REA value (10) will provide a base means of comparison to other types of activity, being defined as the ratio of the calculated average activity acceleration vector standard by the previously calculated average magnitude for the high intensity running.

$$REA_{\boldsymbol{Act}} = \frac{avgMagn(Activity)}{avgMagn(RunHigh)} \quad (10)$$

This will allow student comparison, by reducing the accelerometry data to a single, easy to extract and reliable measurement, independent of physical characteristics and at least to a great extent immune to differences in the devices used for accelerometry capture.

3.4. Illustrative example

The proposed metric was implemented in an algorithm, reading accelerometry datasets, extracting the base REA and estimating the REA value for the activities present in the dataset. The collected school accelerometry datasets was used to assess the REA adequacy to student relative comparison.

Students performed at the beginning of the class the required running activity at high intensity, for a total duration of 8 minutes in order to obtain the magnitude for that activity and estimate a base REA. The teacher controlled student intensity assuring every student was performing the activity correctly. All students started and stopped the data collection simultaneously, and during the school accelerometry data gathering, the start and end times for all activities were annotated in order to correctly separate and extract activities from the dataset.

The REA base value was calculated by identifying the running activity by the timestamps saved in the dataset and calculating the mean of the magnitude for all axes in the defined time period. The rest of the activities were also identified by the saved timestamp and annotated time, and their REA was calculated by dividing the mean of their magnitudes by the previously calculated base value.

Different REA values were obtained for the different activities present in these datasets. For illustrative purposes Table 2 depicts the reported values from a small subset of subjects.

The calculated REA's base values and activity REA's were compared to the corresponding student performance observed in class. The results demonstrate a strong correlation with the observed student behavior in class, with the majority of REA values estimating running, futsal and basketball as the higher intensity activities and volleyball and handball as the less intense activity related to the estimated base value.

Table 2. REA values calculated from the collected school accelerometry datasets

Subject id	Average running magnitude	REA (running high intensity)	REA (normal running)	REA (volleyball)	REA (handball)	REA (basketball)	REA (futsal)
Student1	1.86	1	**1.1**	0.75	0.97	0.77	0.9
Student2	3.13	1	**0.85**	0.63	0.56	0.75	0.69
Student3	19.49	1	**1.59**	0.53	1.25	1.35	1.15
Student4	24.27	1	**0.72**	0.16	0.3	0.41	0.33
Student5	21.75	1	**0.99**	0.4	0.35	0.46	0.52
Student6	11.74	1	0.83	0.35	0.52	**0.89**	0.83

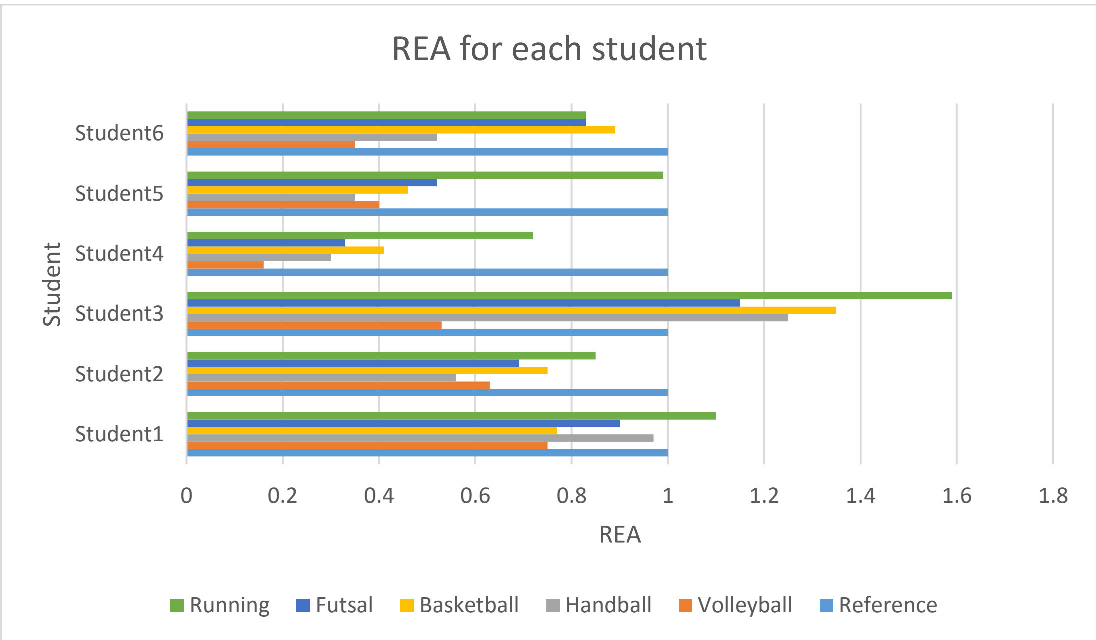

Figure 2 - Chart of the REA values calculated from the collected school accelerometry datasets.

In Table 2 and Figure 2, the calculated REA's for each activity can be compared to the REA value of 1, associating each obtained REA with the maximum intensity provided by the calibration activity.

As it can be observed, student 1 and student 3 performed activities of higher REA than the reference value, which means these students overcame their maximum calibrated intensity. At the time of the implementation of this metric, two data collections had already been completed, which required the students to perform the calibration activity at the end of the class in order to maintain the timings of the previously performed activities. This factor might have affected some student's performance, decreasing their performance, and as a result some student perform better and obtain a higher calculated REA at the rest of activities.

3.5. Remarks

The calculation of REA for each student allows the estimation of an activity related measurement, eliminating the problem of the heterogeneity of devices, and allowing a reliable and detailed student comparison by the teacher. This value, if calculated for each activity, will allow the teacher to evaluate the student performance on each sport, identifying weaknesses and strong points related to the different activities analyzed.

This proposed metric gets some of its inspiration on the metabolic equivalent of task (MET), since it can also provide a measurement that can be used to compare different subjects regarding energy costs in physical activity. The proposed metric replaces the REE of a subject to estimate 1 REA, by the mean of the magnitude of a short duration and high intensity running activity to estimate 1 REA. Posterior activity intensity estimations will ensure that results obtained are related to the student's maximum physical capacity.

To estimate the base REA value, it is required to calculate the mean of the magnitude for a running activity. This activity should be of short duration to ensure a high intensity rate, in order to obtain a precise representation of the student's maximum physical capacity. It is important to ensure the correct execution of this activity by all students. An incorrectly performed running activity for calibration, such as a student running significantly below his maximum capacity, will not accurately represent his activity level and other activity measurements will report a high magnitude and subsequently a good performance by the student with low effort.

This calibration process can be performed at the beginning of the school year, reusing this base value as gold standard of maximum physical capacity throughout the year.

This obtained standard can also be used in activities outside of school, allowing students to compare various performed activities of their choice with their maximum running intensity, or be used as a goal to surpass.

4. Physical Education Class Assessment Tool

4.1. Introduction and features

Physical education classes have been integrated in the Portuguese school systems since the beginning of the 20th century [52]. The same methods of assessment have been used over the last several years, with the teacher evaluating the performance and effort of each student based solely on his observations. This assessment process is hard, as teachers lack tools and information for decision support, which can lead to an unfair grade and student demotivation. Technology advancements allowed the creation of MEMS devices. These devices allow the miniaturization of sensors like accelerometers, allowing the integration in smartphones and other small devices. These lightweight and cheap sensors allow new applications that make use of accelerometry data, to provide feedback on a variety of activities in different areas, like sports, medicine and engineering.

With these applications in mind, we developed a complete assessment tool, making use of student collected accelerometry data during physical education classes, in order to analyze and quantify student effort by extracting several types of information from these datasets.

4.2. Component diagram

This assessment tool is complemented with an analysis module, displaying in the form of charts the student's energy expenditure estimations, the number of steps, student's path, accelerometry axes magnitudes and REA. These charts provide an history of measurements in order to provide an easy way to visualize student activity evolution.

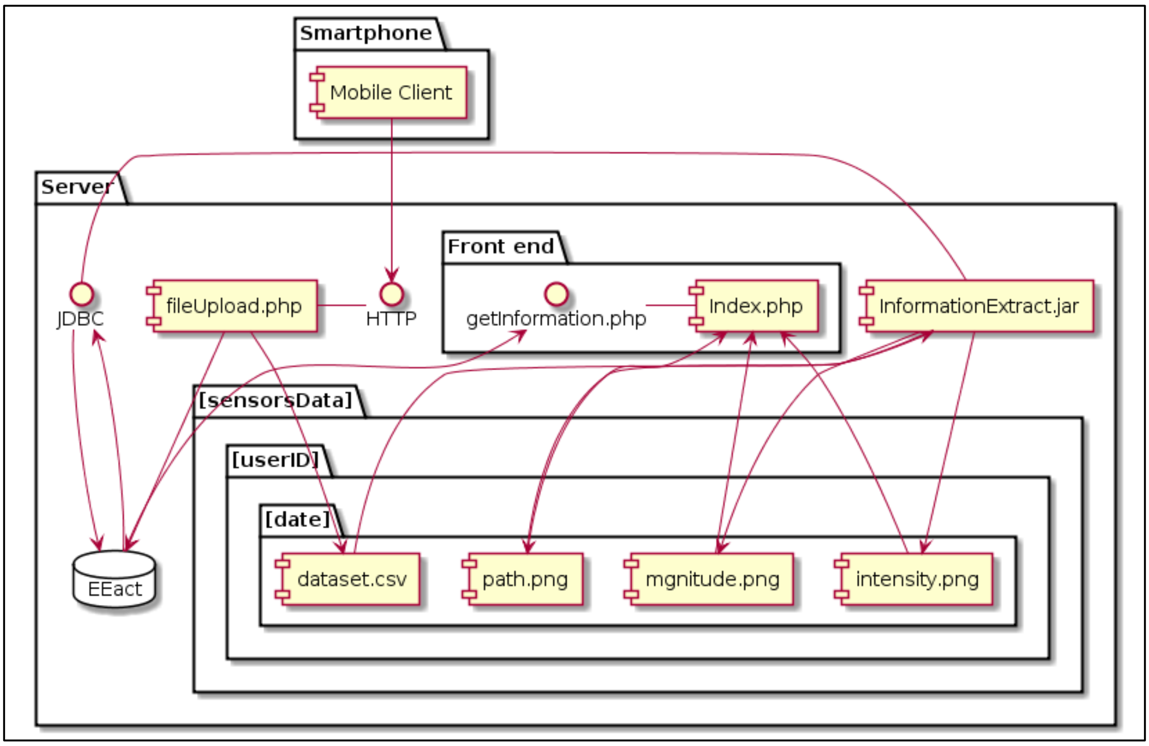

Figure 3 – Component diagram.

This solution will make use of the smartphone application for accelerometry data collection and data upload. The data upload is performed by communicating through REST web services (implementing a client-server architecture), with a PHP script that organizes the received datasets and inserts the user information in the database. The server contains an analysis tool developed in Java that extracts information from the collected datasets, generates various graphs and makes use of the Java Database Connectivity (JDBC) API to insert the extracted information in the database, making all this information available to the frontend web application to display.

4.3. Deployment diagram

We hope this assessment tool may improve not only the evaluation process, but also the children’s motivation towards a greater effort in class and an overall more active lifestyle.
This solution will make use of each student’s smartphone, providing a case for transport and a smartphone application available for free in Google’s play store. Students will use the smartphone application for data collection, requiring only a first interaction in order to complete their user information and to perform the calibration process. Future uses only require them to start and stop the accelerometry collection process. After this process is complete, the application automatically uploads all the available information when a wireless connection is stablished, removing all datasets after they are successfully uploaded and keeping the used space by the application at a minimum.

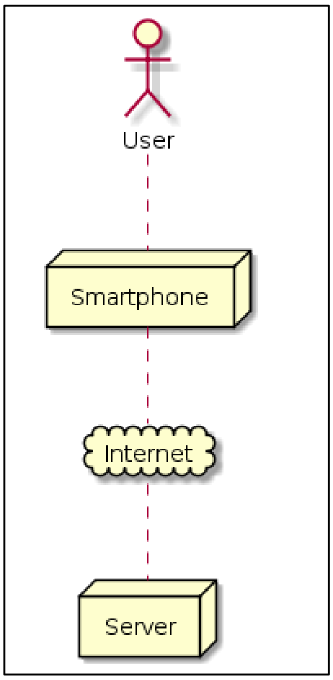

Figure 4 – Deployment diagram.

4.4. Data model

A relation MySQL database is used to store the uploaded student's information, as well as some of the extracted activity information from the datasets. This is used to keep a history of various features and is used by the frontend web application as well as some of the developed algorithms, like EE.

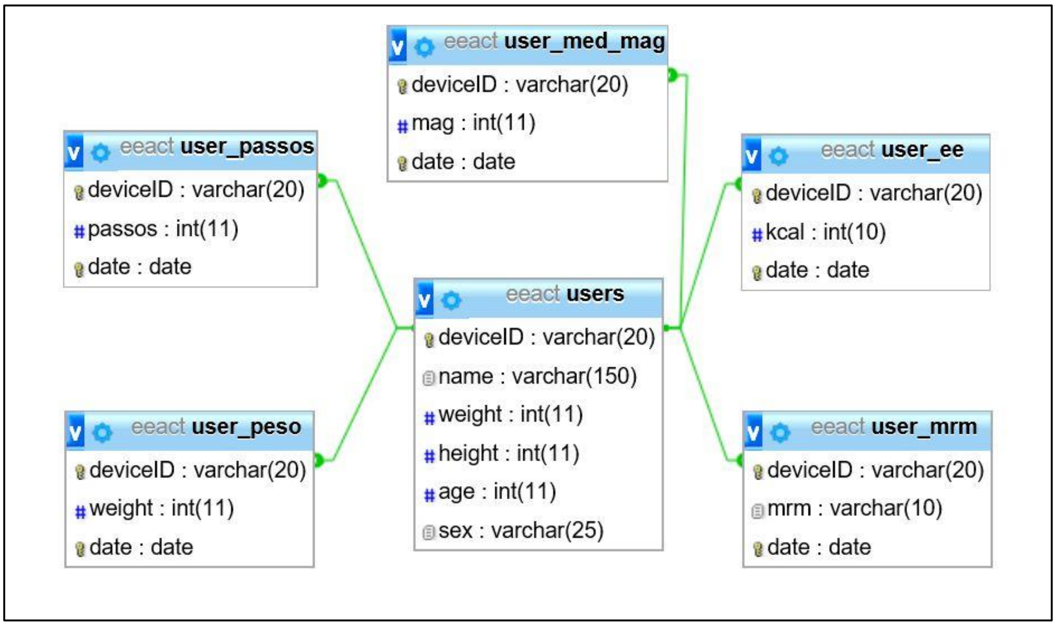

Figure 5 – Database relational model located in the server.

4.5. Mobile Client

To run the application, it is required to complete the subject's information, which is located in the app drawer and is automatically activated on start when the user info is incomplete (see Figure 6). A calibration is required before starting the data collection, since most accelerometer sensors report slightly wrong values (see Table 3). The device's free space is also verified, requiring 75MB, which is an upper estimation for about 90 minutes of sensor data collection.

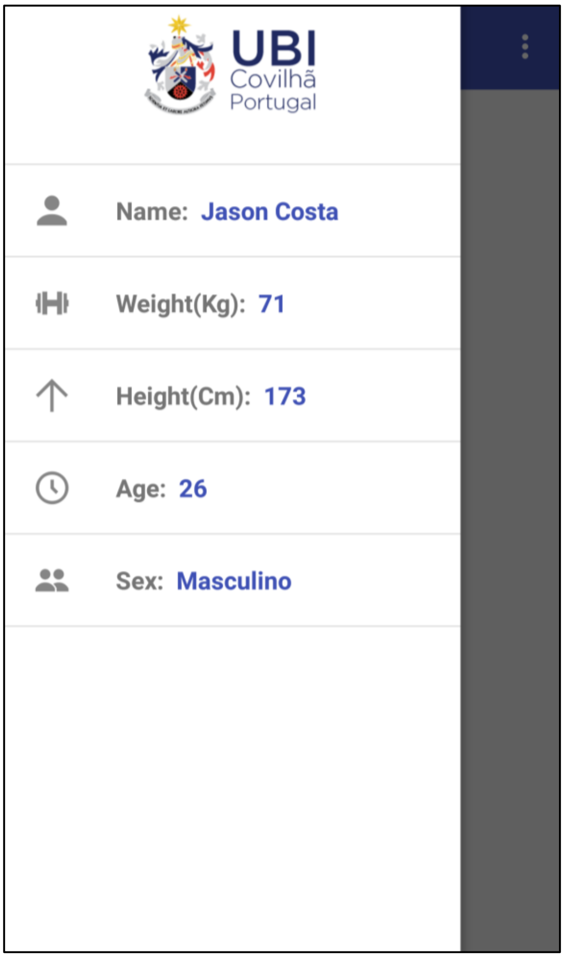

Figure 6 – Mobile client's main screen with the drawer activated.

After these processes have been completed, the user can press start to begin capturing accelerometry values to a CSV file. After stopping, the collected sensor values are immediately uploaded to our server if a wireless connection is available, or kept offline until a wireless connection is stablished which automatically uploads all collected accelerometry.
The mobile client was built for the Android operating system using Android Studio 2.0 and compiled against SDK version 23 (Android 6). It runs on any Android version superior to 2.2 and

was developed with simplicity and usability in mind, to avoid compatibility problems with certain devices and usage problems by the students.

The main smartphone used for testing was a Jiayu S3, running Android 5.1 with a triaxial accelerometer sensor.

The mobile client is used for accelerometry data collection, and to send the collected information to a server. It is composed of a very simple interface, containing a start button, a stop button and a timer (see Figure 7).

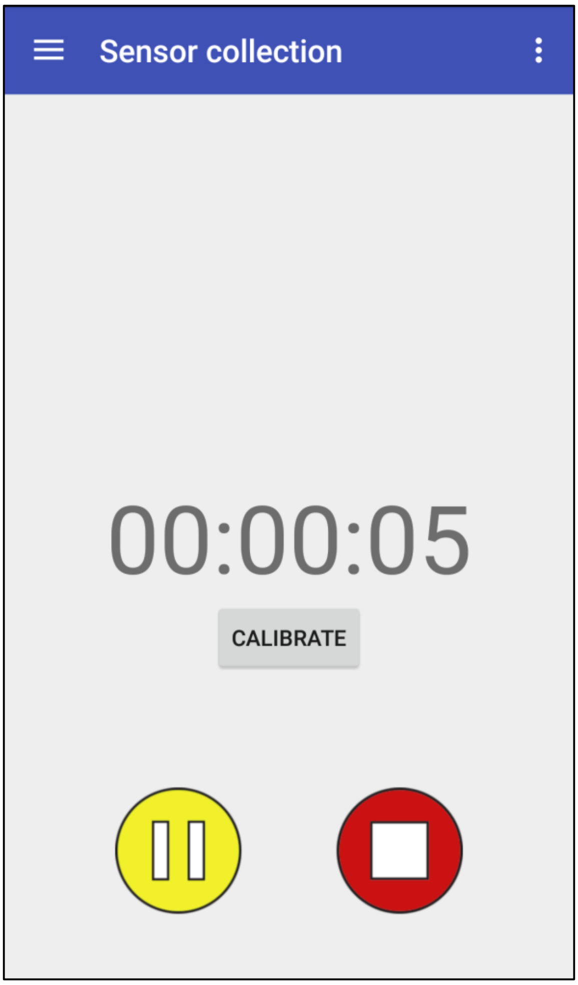

Figure 7 – Mobile client's main screen during accelerometry data collection.

Accelerometer sensor data recording was implemented as an Android service. An Android service can run in the background indefinitely, even if the user starts another application. This allows the developed mobile client to collect data indefinitely until the user presses stop. This service is also efficiently managed, keeping an internal service state and recycling its resources when the activity is stopped and the data collection is not running.

Sensors become inaccessible after the CPU enters the sleep state [53], being necessary to keep the device's CPU awake for the data collection by keeping a wake-lock until the user presses stop.

The accelerometer sensor availability is checked prior to data capture. If the device has an accelerometer, the device will register the sensor with priority SENSOR_DELAY_FASTEST. The priority defines the number of samples to retrieve from the sensor, which in this case will retrieve as many as possible. In the main device used for testing, a sample rate of 90Hz to 150Hz was observed, resulting in 90 to 150 accelerometry samples per second. This sample rate was chosen since a high sample rate is needed for testing and for algorithm development.

Artifacts were removed from the sensors' values, since large value spikes were observed in some devices. These were eliminated by removing all values bigger than the provided sensor maximum range, which is a method available in the Android API. Sensor values are also low-pass filtered in order to smooth the data. Different devices were tested for their accelerometry values, since different smartphone devices have different sensors, and even the same sensor can be factory calibrated differently. The calibration process is necessary since in our tests, most devices reported different values when placed with the screen up in a flat surface. A calibrated accelerometer placed flat on a surface should only report the value of gravity of $9.81\mathrm{m/s^2}$ on the vertical axis and no acceleration on the other axes [51].

The different values of the tested devices are reported on Table 3.

Table 3. Accelerometer values for different devices placed flat on a surface

Device	**Accelerometer values**		
Jiayu S3	$\mathbf{x}\!:\ -\mathbf{0.1m/s^2}$,	$\mathbf{y}\!:-\mathbf{0.1m/s^2}$,	$\mathbf{z}\!:\mathbf{9.81m/s^2}$
Samsung galaxy S3	$\mathbf{x}\!:\mathbf{0.1m/s^2}$,	$\mathbf{y}\!:-\mathbf{0.7m/s^2}$,	$\mathbf{z}\!:\mathbf{9.3m/s^2}$
Wiko Fab 4G	$\mathbf{x}\!:\ -\mathbf{0.2m/s^2}$,	$\mathbf{y}\!:-\mathbf{0.2m/s^2}$,	$\mathbf{z}\!:\mathbf{9.7m/s^2}$
Samsung galaxy fresh	$\mathbf{x}\!:\ -\mathbf{0.2m/s^2}$,	$\mathbf{y}\!:-\mathbf{0.3m/s^2}$,	$\mathbf{z}\!:\mathbf{8.2m/s^2}$
Tablet Rockchip	$\mathbf{x}\!:\ \mathbf{0.15m/s^2}$,	$\mathbf{y}\!:\mathbf{0.15m/s^2}$,	$\mathbf{z}\!:\mathbf{4.9m/s^2}$

The calibration process asks the user to place the device in a flat surface, automatically detecting this position in order to assure a correct calibration. To detect this position even on smartphones that report slightly incorrect values, a threshold was defined for the vertical and horizontal axis, defining a range of accelerometry values in which this position can be detected. This calibration is performed by calculating the difference between the reported values for all the three axes and the expected gravity value on the vertical axis. The calculated offset is saved in the Android settings manager and is used for all future accelerometry data collections. A similar calibration process is implemented in R. Guidoux et al. [7]

The calibration process takes 5 seconds, with a visual feedback of colour change, from orange to green, indicating the calibration progress (Figure 8).

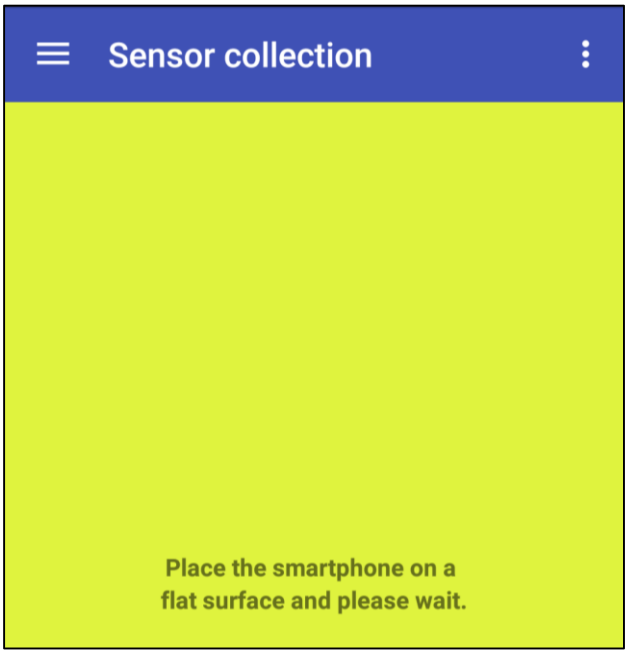

Figure 8 – Calibration process of the mobile client.

During data collection a notification is displayed with current sensor values (see Figure 9). From the collected sensor values is automatically subtracted the calculated offset from the calibration process. This guarantees more accurate results in the extracted activity information between different devices.

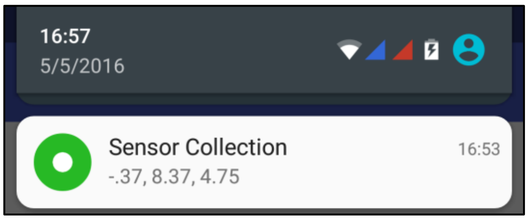

Figure 9 – Notification during accelerometry data collection on the smartphone.

A set of folders is created prior to capture, followed by a file with the current date. If a data collection was previously performed on the same day, the collected values will be added to the end of the same file. These files and folders are created in the documents folder of the external SD card if available, otherwise they are created in the internal memory. Files are kept offline until the server reports a successful upload.

Accelerometer values are stored in a comma-separated file, in the following format: “x;y;z;time”. This represents the three axes acceleration values and a timestamp of the current time reported by the device on the time of collection, which will be used to identify the time period for the extracted information and to identify the performed activities.

The resulting dataset is immediately uploaded on stop if a wireless connection is available or automatically when a wireless connection is established, through the implementation of an Android broadcast receiver. The information sent to the server is composed of the collected accelerometry dataset and a JSON containing the user info and an Android device id composed of a 64 bit number represented in hexadecimal (see Table 4), which uniquely identifies the device and is provide by the Android API.

Table 4. JSON example of the uploaded user information in plain text


```
deviceInfo {2}
    sensor_type : Accel
    device_id : 9781cf5e8a40a540
userInfo {5}
    height : 173
    name : Jason Costa
    age : 25
    sex : Masculino
    weight : 20
```


The user personal information is encrypted using the RSA public-key cryptosystem with a key size of 1024 bits. All the user personal information sent in JSON format is encrypted using the server's public key (see Table 5).
This guarantees privacy of the information sent across the network.

Table 5. Server's public key


```
-----BEGIN PUBLIC KEY-----
MIGeMA0GCSqGSIb3DQEBAQUAA4GMADCBiAKBgH+K17wpy6MK/wNREyHwLF1vBxjJYKIJY7hdqnojVH1Izrb
C85OAsqFmTM2qP/EfMFy9F5Ua1iEg0p46LO7AAZKfxE8GFKdpFLNKCcrBHgLKz1kAdziXju16ExcDNzlMU+g3
HNwQbjdcXxQnaXkjrPj8oEnl9jKe3A5ROTViwMtjAgMBAAE
-----END PUBLIC KEY-----
```


4.6. Backend and Frontend

The server side is composed of a frontend web application to visualize the extracted information, a script for data upload and a relational database (see Figure 5) to save user information and extracted activity information from the datasets. The data upload script was written in PHP, and is completely autonomous, creating the required folder structure (Table 6), inserting user info in the database and moving the received files to the appropriate locations.

Table 6. Server folder structure

/sensorsData/accel/device_id/DD-MM-YY.csv
/sensorsData/accel/device_id/DD-MM-YY_2.csv
/sensorsData/accel/device_id/DD-MM-YY_3.csv

Each subject has a folder identified by his device id, that contains his uploaded datasets grouped by day. When uploading a new dataset, if a dataset for that specific day already exists a number increment is appended to the dataset filename (see Table 6).

The user information is saved in a MySQL database, keeping a history of the user's weight, steps, EE, the mean of the magnitude and the REA for each day (see Figure 5 in section 4.4.).

The frontend was built using AngularJS and Bootstrap, creating a lightweight and responsive single page web application. The frontend displays a list of all the users available in the server, allowing an instant search by name. By clicking a user, his activity related information is displayed, including graphs for EE, weight and REA. Figure 10 depicts a screenshot of the frontend.

Figure 10 – Frontend application with a user selected.

It is also possible to consult individual information for a given day. This information includes the mean of the magnitude for all axes, the number of steps and path estimation (Figure 11).

Figure 11 – Search by date available in the web application.

By selecting a different user, the same information for the same selected date is displayed, allowing quick comparison.

4.7. Analysis tools

A wide range of activity related information is presented in the form of graphs. These graphs help to analyze and assess student physical activity and evolution over time, by providing an history of various measurements.

Graphs are generated from extracted information from individual datasets for an entire day, and are generated natively by multiple algorithms implemented in Java. The information extracted by these algorithms is also inserted in the database, and associated with a subject and a date, in order to generate history graphs for various features using Google charts.

The developed algorithms natively generate the following graphs from accelerometry datasets:

1. Number of steps;
2. Subject path;
3. Mean of the magnitude for all axes combined;
4. Mean of the magnitude for each individual axis;

The history graphs containing multiple days of information include:

1. Energy expenditure per day;
2. Mean of the total magnitude per day;
3. Total REA per day;

For all graphs the developed algorithm needs to iterate over all folders, reading all datasets from each day and extracting and calculating the required features.
The generated graphs can create images of big dimensions depending on the dataset used for information extraction. Use of the Java's buffered image class is not possible, since there exists a size limit defined by Java's max integer value for image construction. During development this value was easily reached, causing an out-of-memory exception. To go around this limitation a library named PNGJ [54] was used for high performance image encoding with virtually no size limits.
During development, all analysis tools were tested on a dataset composed of running at moderate pace, walking at a normal pace, and resting for 24 minutes (see Table 7).

Table 7. Dataset and device used for testing

Dataset	Device	Activity	Time
1	Jiayu S3	Running, walking and resting.	24 minutes activity (5km) + 24 minutes resting.
2	Jiayu S3	Resting	52 minutes.

Table 8. Activity periods for dataset 1

Dataset	Activity	Periods	Dataset
1	Running	16:39 to 16:48 17:11 to 17:21	1
1	Walking	16:48 to 17:11	1
1	Resting	17:21 to 17:45	1

4.7.1. Intensity graph

For the intensity graph, an open-source step detection algorithm was implemented [55] in order to detect the total number of steps for each dataset. This algorithm aggregates sensor values, finds both maximum and minimum and compares the difference to the defined sensibility value. The intensity is defined by the number of steps each second, drawing the graph accordingly with the obtained value. The number of steps performed was also measured with a MI band, which is a fitness tracker made by Xiaomi. The reported number of steps by this device was used as a reference value, adjusting the sensibility of the algorithm until a number of steps close to the reference values was achieved. After some testing, we used a value of 10 as a sensibility threshold in order to detect a number of steps close to the reference values (see Table 9). The generated graph displays an average number of steps for each second, which is also identified by a color that represents the intensity (see Table 10). This graph also includes a timestamp at the bottom to identify the activity period and the number of steps on the left as seen in Figure 12.

The intensity chart generated an image of size 3291x843.

Table 9. Reported steps for the intensity algorithm against reference values

Steps	Device
5291	Mi Band
5489	Algorithm (threshold = 10)

Table 10. Intensity detection values used in the intensity algorithm

Number of Steps	Defined intensity	Graph color
0 to 2	Low	Blue
2 to 4	Medium	Orange
4 or more	High	Red

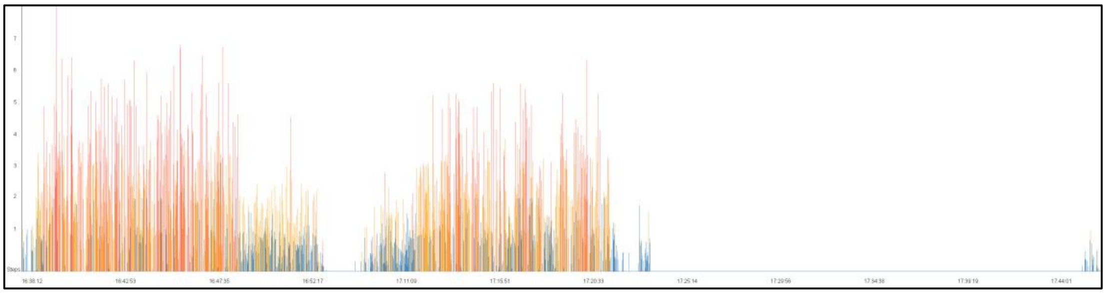

Figure 12 – Generated intensity graph for dataset 1.

4.7.2. Subject's path graph

The subject's path is drawn based on the previous step detection algorithm and horizontal axis analysis. The developed algorithm performs a horizontal axis magnitude analysis, detecting direction changes through the acceleration differences in the horizontal axis. This algorithm makes use of the previously implemented step detection analysis to draw the line further in the calculated direction. Each direction change detected is represented as a 90º curve. The algorithm makes use of a specified threshold to detect direction changes, analyzing horizontal acceleration until a defined number of consecutive values above or below the threshold is read (see Table 11). Negative acceleration values represent a left rotation and must be below the negative threshold specified, while a positive acceleration means the subject is rotating to the right and must be above the positive value defined. A subject rotating slowly might generate some values below the defined rotation threshold. A certain number of invalid values between that threshold among consecutive valid values is allowed in order to help the detection of the subject's rotation.

If all these condition are met, a direction change is performed to the detected direction, saving the new position that the subject is facing (see Figure 13).

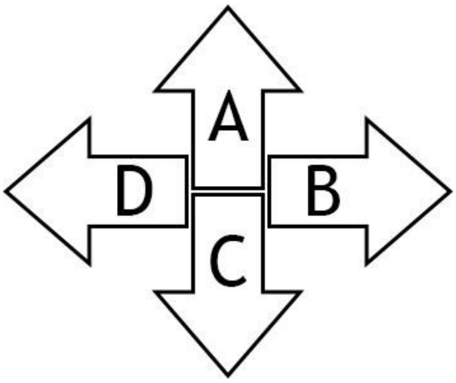

Figure 13 – Current direction identification

Table 11. Algorithm parameters for optimal direction change detection

Variable	Optimal Value	Description
Threshold	6	Defines the value for which a horizontal acceleration is considered a valid direction change.
RepeatInterval	10	Defines the number of successive values above threshold.
MaxErrors	3	The max number of values between the threshold among consecutive valid values.

The subject's activity start position is identified with a blue square and the end of the activity with a red square as seen in Figure 14. The chart image size increases with activity intensity and duration. The parameters used greatly define the final graph, with high repeat intervals or low threshold delivering a straighter line path, and the opposite drawing a great number of direction changes.

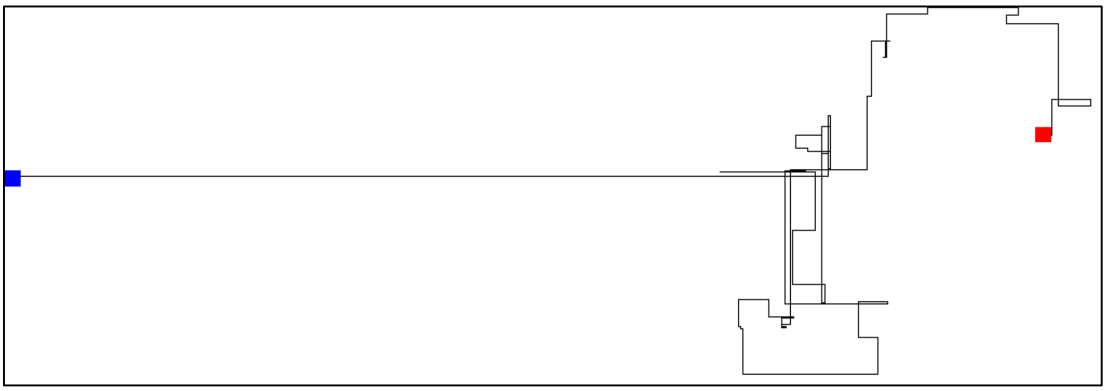

Figure 14 – Subject's path graph for dataset 1.

4.7.3. Magnitude graphs

Providing a way of visualizing each axis acceleration is important, since it can provide detailed information about the subject's movement, like jumping, sprinting and direction changes. To provide this, the magnitude for each axis was calculated, averaging the results per second of data as well as the mean magnitude for all axes combined.

$$mag_{axis} = \sqrt{\mathrm{A}_{\mathrm{axis}}^2} \tag{11}$$

$$mag = \sqrt{\mathrm{A}_{\mathrm{x}}^2 + \mathrm{A}_{\mathrm{y}}^2 + \mathrm{A}_{\mathrm{z}}^2} \tag{12}$$

In the graphs that make use of the vertical axis, the gravity must be removed in order to only report the subject's acceleration. The vertical axis represents vertical accelerations performed, like jumping (see Figure 15).

The lateral horizontal axis Y, represents lateral acceleration, providing rotation and direction change information (see Figure 16).

The Z axis, provides frontal horizontal acceleration, represents acceleration parallel to the ground, like running or sprinting (see Figure 17).

The combination of all three axes provide an overall visualization of the total acceleration of the subject (see Figure 18). The mean of the magnitude for all axes combined is calculated for the entire dataset, saving the value in the database along with the subject id and the corresponding date to create an history graph of user acceleration magnitude for each day (see Figure 20), providing a way to visualize subject activity acceleration magnitude evolution. Since this magnitude also includes the vertical axis, therefore the element of gravity, gravity was discarded using a low-pass filter.

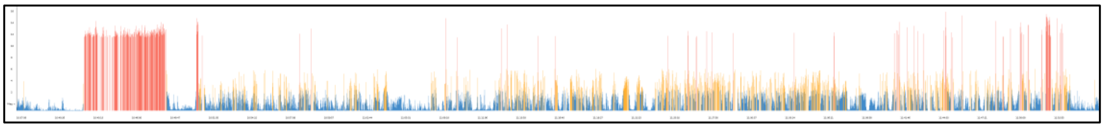

Figure 15 – Magnitude chart for the vertical axis X, with gravity removed.

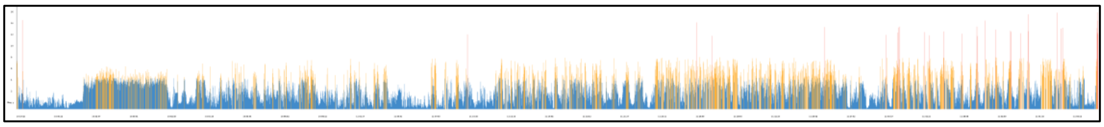

Figure 16 – Magnitude chart for the lateral horizontal axis Y.

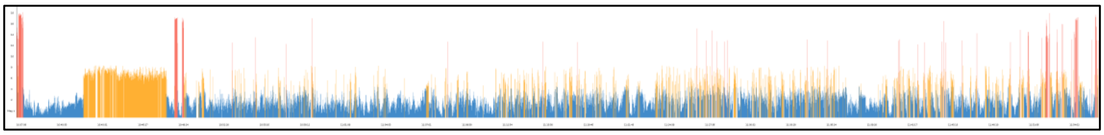

Figure 17 – Magnitude chart for the frontal horizontal axis Z.

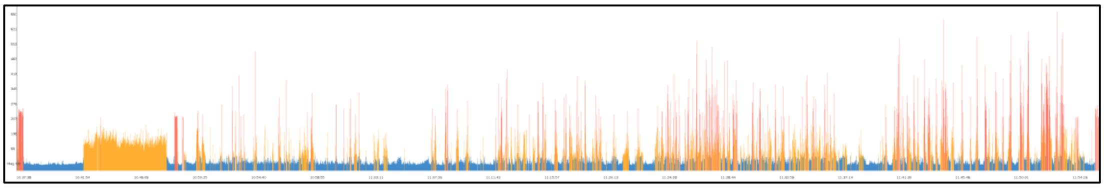

Figure 18 – Magnitude chart for all axes combined.

4.7.4. Weight, REA and EE graphs

The weight and energy expenditure (see chapter 5.2) graph display a history of these two related values as seen in Figure 19. During the data upload processes, user information like age, sex, height and weight is sent to the server. The weight is updated after each upload, keeping the previous value along with the corresponding date and subject id, creating a history of weight changes represented by a blue vertical bar. Energy expenditure is estimated for each dataset, making use of the available user's information (weight, height, age and sex) combined with accelerometry values to estimate EE and is identified by a red vertical bar.

The proposed REA metric is calculated for each dataset, inserting the produced results in the database, with the corresponding dataset collection date and subject id, allowing the creation of a REA history graph to analyze overall activity evolution.

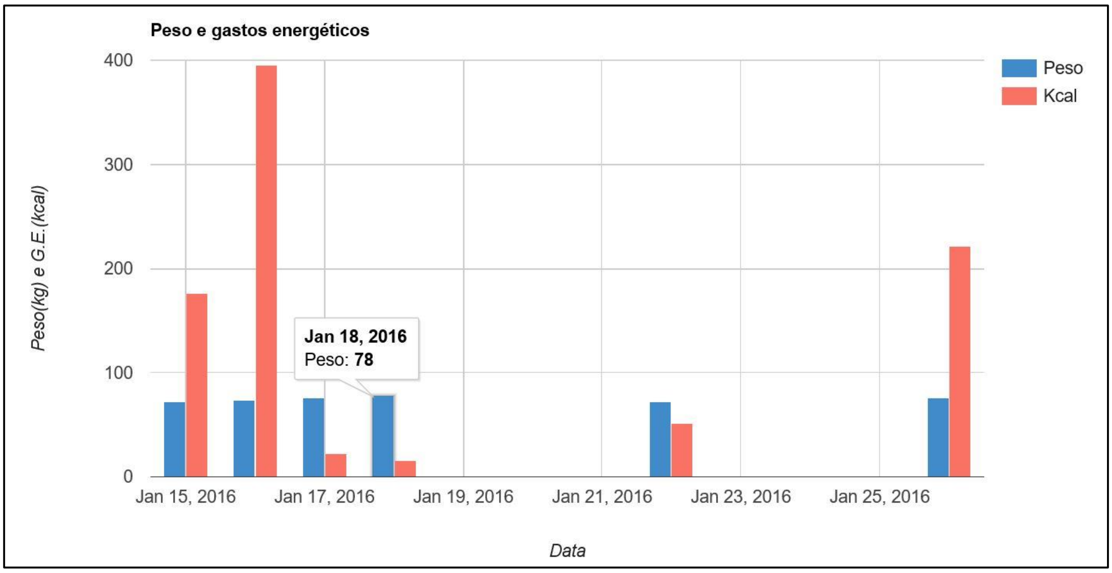

Figure 19 – Weight and EE history chart.

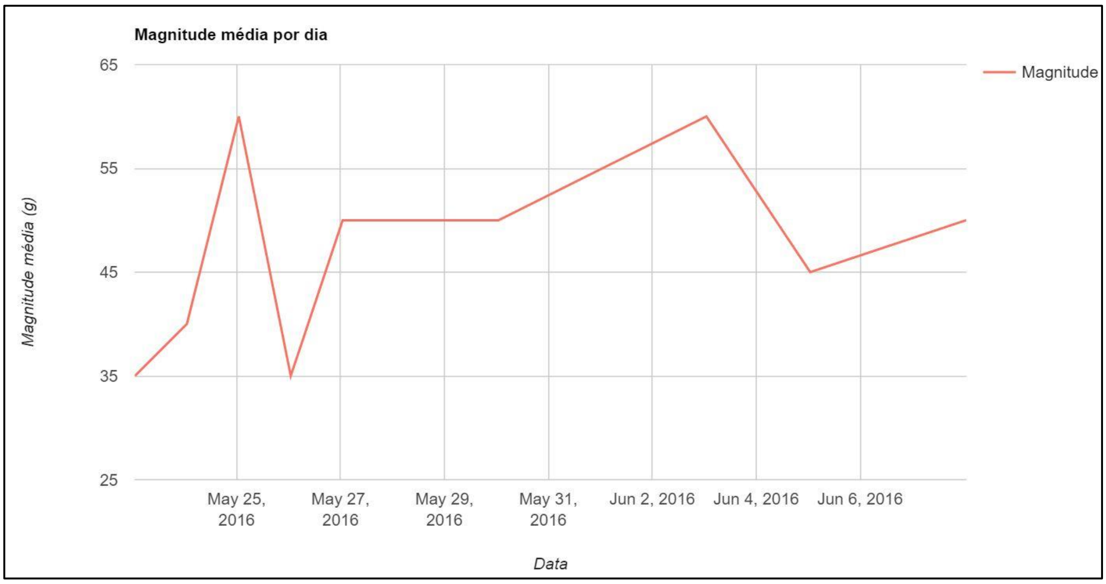

Figure 20 – Chart of the Mean of the magnitude for each day.

4.8. Remarks

The presented analysis tools were developed in order to create new methods of extracting and visualizing information from accelerometry data. These tools are an important part of this solution and a great deal of effort was put into determining the best ones to evaluate student activity over time. The developed tools present a reliable set of activity information graphs to be used in student assessment. The implemented step detection algorithm produced good results for the tested activities, but the sensitivity defined for step detection might need to be adjusted, since different devices used for accelerometry data collection might have different sample rates or different precision. Some of the devices tested collected accelerometry data at lower sample rates, which could result in less accurate results when compared to higher quality devices. The calibration of the step detection algorithm against a state-of-the-art device like the MI band was an important step to ensure more accurate results.

User privacy is an important aspect to consider. The current implementation guarantees privacy for the user personal information, but not for the accelerometry dataset. If an attacker can capture a dataset and identify its user, a great amount of information can be extracted since this dataset contains activity and time information. In a future implementation, the dataset will also be encrypted along with the user's personal information. The used public-key RSA cryptosystem is not optimal for large data encryption, since it will increase the size of the final cryptogram, wasting space. It is also slower compared to symmetric encryptions systems. Usually both methods are combined, using public key cryptography to exchange a unique symmetric key for data encryption and exchange. This cryptosystem was chosen due to its faster implementation, and because the data transmitted is very small, being on average 116 bytes.

The resulting cryptograms are also always different even for the same messages, since the padding mechanism used adds randomness [56].

The analysis tools were successfully developed and implemented, with the developed algorithms providing a precise representation of subject's acceleration on all axes through time according to the physical education class observations and the corresponding activity list, demonstrating the effectiveness of using an accelerometer in these two kinds of data extraction and visualization. The mean of the total magnitude for each day provides an effective and easy way to visualize subject activity intensity, proving to be a great means to evaluate the subject's activity evolution over time while the REA provides activity values related to a base running activity, and is designed to be used in a multiple subject comparison scenario.

The subject's path graph was an experiment in order to measure the effectiveness of using accelerometer data to represent direction changes. An accelerometer can only can gauge the orientation of a subject with relation to the Earth's surface, not providing enough information to accurately detect user direction. The addition of a gyroscope would improve this detection, since gyroscopes allows the calculation of orientation and rotation, being able to measure the rate of rotation around a particular axis. This algorithm proved effective in detecting fast direction changes, but isn't precise enough to draw a subject's path accurately.

5. Physical Education Class Dataset

5.1. Introduction

To develop and test the effectiveness of the proposed student assessment solution, accelerometry data from the target demographic group in the context of physical education class was required. The accelerometry datasets used for this research were collected by implementing a data collection prototype in a school, providing valuable feedback about the mobile client's compatibility with multiple devices, identifying possible improvements in the mobile client and the data collection process by comparing differences in a variety of accelerometer sensors and allowing the creation of an accelerometry dataset during multiple activities performed by different subjects.

The prototype was implemented in the school "Escola Básica 2/3 do Tortosendo", with the help of Professor Filipe Ferreira, who lectures physical education to two classes of the 8th year of the Portuguese education system. Professor F. Ferreira provided valuable feedback regarding the proposed assessment tool's features, identifying the most useful statistics to use in his student's assessment. He also conducted the data collection process, by building the activity list (see Figure 34), and guiding his students throughout the process.

Both his classes accepted to participate in this study, making a total of 13 students for class A and 12 students for class B. The student's parents were given a document to sign explaining the nature and objectives of this study, mentioning the requirement of using the student's smartphone during physical activity class, as well as mentioning the absence of any risks concerning the participation. Only one student was not allowed to participate. Some others subjects were given permission, but unfortunately didn't have a required Android smartphone and couldn't participate.

To prepare the prototype for the accelerometry data collection, a first visit to the school was made during a physical education class, lectured by Professor F. Ferreira. In this class, a brief presentation was made explaining the objectives of this experiment, how the accelerometer sensor present in their phone can be used to collect and classify their activity level, and how the teacher can make use of this information to improve their assessment. Students provided their smartphone for the mobile client installation, configuration and testing, being guided through the process. All steps were completed successfully by all students, having installed the mobile client, calibrated the accelerometer, collected accelerometry data for some brief moments and uploaded it successfully. All students had the required free space of 75MB.

Two students weren't able to perform the calibration available in the mobile client. This calibration process detects the action of placing the smartphone screen up on flat surface. As a result of the smartphone providing very uncalibrated values, the algorithm wasn't able to detect this position. This was solved by providing a new version of the mobile client, which provided a larger threshold for the detection of this position, allowing them to participate in this experiment.

The developed mobile client was installed and configured in a total of 25 devices. The prototype implementation and first approach to the students was successful. Almost all students had the required Android smartphone to participate in this experiment, and the mobile client performed without problems in all of the available smartphones. The students were participative and autonomous during the mobile client install and testing, demonstrating interest in this study and requesting access to the final extracted information in order to compare results between each other. One of the main objectives of this solution is to increase student motivation, which was observed in this first phase.

5.2. Protocol

After the successful prototype implementation during the first school visit, three data collections were scheduled. Accelerometry data was collected a total of three times, one for class A and two for class B, making a total of 60 minutes for class A and 120 minutes for class B. The data collected twice for class B will allow to analyze student evolution between different days, in order to better evaluate the effectiveness of this tool for the proposed goal of student assessment.

The activity list was composed by Professor F. Ferreira, who also conducted the data collection process, guiding the students throughout the whole class, instructing them when to start and stop the mobile client, and helping them perform the various activities.

The activity list is composed of a total of five different sports: running, volleyball, handball, basketball and futsal. The accelerometry data was collected while performing team matches of equal team sizes and match length. A smartphone bag was provided to each student in order to carry the smartphone at the waist. After some analysis and testing, this was identified as the best choice to place the smartphone, capturing accelerometry data with greater precision as already reported in the literature [3], [9], [10], and being the most comfortable during activity execution. As depicted in Figure 22, the smartphone must be placed with the back facing forward, it’s top pointing left, and placed in front of the subject in order to correctly identify the position of each axis.

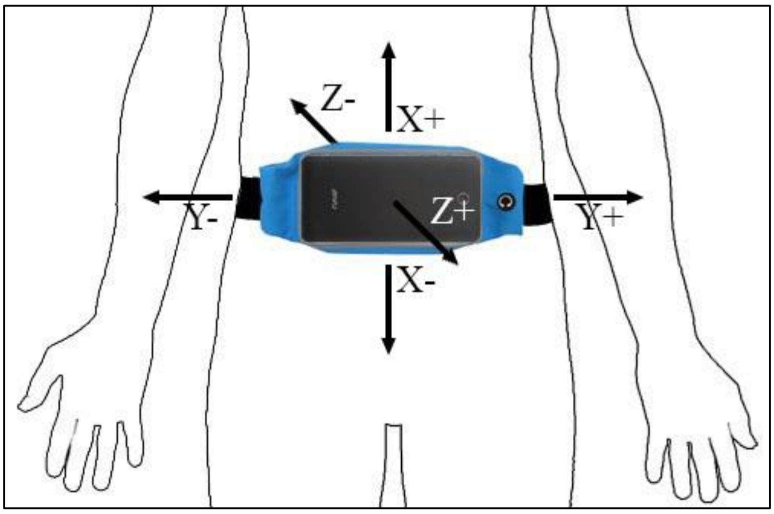

Figure 21 – Smartphone position during data collection.

All students started and stopped the data collection simultaneously, allowing an easier and more accurate activity and information extraction and comparison. The entire class was recorded without interruptions, identifying each activity by time and collecting a single dataset containing all pre-defined activities (see Table 12). Each activity performed is preceded by a two-minute explanation of the next activity to perform. The physical education class in which the data collection was performed had a total duration of 90 minutes, from which 60 minutes of activity was collected, with 10 initial minutes for preparation, 10 final minutes for stretching and 2 minutes between activity for resting and instructions. At the end of the class, students stopped the data collection. The collected accelerometry data is kept offline until they connect to a wireless network, which automatically uploads the data. Datasets were successfully received for 18 students, 10 from class B and 8 from class A, being on average 25MB of size for all subjects. Some datasets were not received, possibly due to problems during collection, since it was not possible to verify the integrity of each dataset at the end, or caused by a failed upload, due to the absence of a stable wireless network. The subject's information regarding weight, age and height become immediately available in the web application, while other statistics like the number of steps or the mean of the magnitude only become available after the accelerometry datasets are processed.

Table 12. Activity list

Activity	Duration	Description	Activity
Activity 1	8 minutes	Running followed by stretching.	Running + stretching
Activity 2	13 minutes	Team match (3x3)	Volleyball
Activity 3	13 minutes	Team match (3x3)	Handball
Activity 4	13 minutes	Team match (3x3)	Basketball

Activity 5	13 minutes	Team match (3x3)	Futsal

5.3. Equipment

The student's devices used for accelerometry data collection, consisted on low to medium range devices. The Android OS might pause, stop or destroy applications when resources like available RAM are low. Since the mobile client sensor collection was implemented as a foreground service, the system will prioritize it over any other running applications and it will not be made a candidate for killing on low memory. The mobile client was tested prior to the school prototype implementation, by testing it successfully on low-end devices for long periods of accelerometry data collection, making the mobile client suited for low-end devices. The accelerometer present in the smartphones is also very important, since a low quality accelerometer will report incorrect values, which might produce inaccurate or low precision results. Determining the quality of these sensors is hard without a previous analysis of the device, and although the performed calibration can fix small reported values, very low-precision accelerometers cannot be corrected. A hard aspect to evaluate is accelerometer sensibility to acceleration. Different devices may report different acceleration values for the same movement, even if calibrated correctly.

Overall, the student's smartphones performed very well for data collection and information extraction.

Table 13. Smartphones used for accelerometry data collection

Subject ID	Smartphone
3edd46b12a4a989c	Samsung Galaxy Grand Prime
4a38ac6ce7a86aa6	Meo Smart A80
4dc0deb9b208b99a	LG L5
35f590bd8ca5f2	Wiko Star
a82f8795be09f07a	Samsung Galaxy Grand Prime
c7d4a18bf9794080	Meo Smart A30
f38e79f69bf5301f	Samsung Galaxy S3
786a6f875a2882a3	Samsung Galaxy Core Plus
b331d12163ebe02f	Wiko Star
564d438fdcc8292d	E-Star X40
9769b244b6ba9806	LG E610
9101a2995e1623ea	ZTE A40
e801815d0494a18c	Dooge F5

fafa678fb19095c0	Samsung Galaxy Grand Duos
ef9706aef0f7bb47	Sony Xperia M2
7efa121adf7347da	LG L Bello
892406421bf9a3e0	Samsung Galaxy Grand Duos
4c4979cdb1d3a2b2	Umi Emax Mini

5.4. Population characterization

The population in this study was made of students attending the 9th year of the Portuguese education system. Their characteristics can be observed in Table 14.

Table 14. Sample characterization
Mean values ± standard deviation and ranges (minimum to maximum); n = number of subjects;

	Men (n=11)		Women (n=7)	
Characteristics	Mean±SD	Range	Mean	Range
Body mass (Kg)	57±12.6	45 - 80	56±6.9	45 - 65
Height (Cm)	165.8±8	150 - 189	150.9±7	152 - 167
Age (Years)	14.8±3.1	13 - 17	13.8±0.8	13 - 16

5.5. Remarks

The accelerometry dataset collection protocol was thoroughly studied and tested before applying the prototype in the school, since access to the subject’s smartphones for debugging and testing was limited. One of the most important aspects of development was to create a solid mobile client for accelerometry data collection, making sure that all different smartphones were compatible and performed as expected. Testing with different smartphones in mobile development is important, but unfortunately due to access to a limited range of devices, this was not possible. Due to time constraints, data collection was limited to three classes, which limited testing and debugging in the physical education class environment, resulting in some data loss caused by reasons that were difficult to determine. Nevertheless, with all present constraints, the prototype and data collection were successful, with no students reporting discomfort in using the waist mounted smartphone, and allowing the collection of a reasonable number of accelerometry datasets. The server was also able to handle all simultaneous connections without problems.

Since the target group that will use the mobile client are children, simplicity and ease of use was an important point to consider, which is why automatic upload was an important feature to implement. This guarantees that the collected data is automatically sent as soon as a wireless connection is available, deleting the files after a successful upload. The means of transportation of the smartphone was also carefully considered, since it must be kept safely secured to the student, being comfortable to transport during activities and provide accurate subject acceleration data. The students reported no discomfort with the used means of transportation. The activity list developed by Professor Filipe Ferreira contained 5 different sports activities, allowing an interesting comparison between accelerometer readings and intensities. This dataset relies on sensor data captured on different devices with different accelerometer sensors, which is an important aspect in research that aims to develop robust solutions that targets different devices. One of the main goals of this work is to build an accelerometry dataset collection, making it available to the community for information extraction and activity recognition (Appendix A shows the dataset description that can be obtained from http://193.136.67.246/~jason/physical_education_class_accelerometry_dataset.zip). The captured datasets are provided for free, composed of several unique activities performed by children, identifying the physical demographic characteristics and devices used by each one. The collected data will be anonymized according to international standards and the operating Portuguese legislation, in particular according to law n. º 67/98 of October 26.

6. Illustrative Experiments and Results

6.1. Introduction

In this chapter, the experiments performed using collected accelerometry datasets are discussed. We prepared and developed these experiments on collected accelerometry data for simple activities like walking, running and resting, providing a simplified set of data to work with. After developing the prototypes, we apply them to some samples of the physical education class accelerometry datasets, comparing the estimated values for each subject with an estimated reference value.

This chapter will begin with energy expenditure estimation (EE), using accelerometry data and state-of-the-art EE equations. The equations extracted from the literature are implemented, estimating EE from raw accelerometer values and subject's physical characteristics like weight, height, age and sex. In the second part, activity recognition is performed using Weka, experimenting with different classifiers, extracted features and window sizes, in order to assess the effectiveness of using accelerometry data for activity recognition. This comparison provided information about the best window sizes, features and classifiers to use when classifying this type of data. All experiments have a corresponding table of results, with the best values identified in bold.

In the end we discuss the results obtained and possible improvements.

6.2. Energy expenditure estimation

Energy expenditure estimation is an area of extensive research and applications [8], [9], [30], [39], with many algorithms developed using a variety of data sources. These data sources might vary from sensor information [9], estimation from activity performed, activity duration and intensity. The signals used might be used independently or combined [14], using accelerometry data provided by an accelerometer or real time global position and elevation, by GPS. This global position can also be used to calculate distance, speed and altitude change, providing a very complete set of information for activity intensity and EE estimation. Numerous mobile apps already use these signals to estimate a variety of activity related information including EE, like Google Fit [42] and Endomondo sports tracker [57].

Mobile fitness tracker apps deliver an estimate of EE that changes according to the activity performed. These applications require the previous selection of the activity, as well as the user's age, sex, weight and height to get an estimate based on the final duration and intensity of the workout, e.g. the Endomondo sports tracker [57]. This intensity is typically calculated for outdoor exercises like running and cycling, and uses distance travelled over time, using GPS

positioning. Some applications like Google Fit [42] automatically estimate energy expenditure, activity duration and identify the activity performed based only on accelerometry data and making use of machine learning [58]. These algorithms are proprietary and not made public.
In our implementation, the equations provided in K. Y. Chen et al [9], are used to estimate EE using tri-axial accelerometry data. Two equations are provided for EE estimation, one linear and one non-linear. These equations are meant to be used with accelerometer counts, which are a proprietary measurement delivered by devices like the *Tritrac-R3D*. These equations also take input parameters, see equations (3), (4), (6), (7), (8) and (9), dependent of subject's body weight, height, sex and age. These equations estimate EE for a given minute, expressed in kilojoules (kJ).
An algorithm was developed to estimate EE implementing the previous equations. It starts by fetching the user's information from the database in order to calculate the equations parameters. It then reads the entire collected dataset for the corresponding subject, collecting samples for each minute and adapting the accelerometer raw samples to an estimation of accelerometer counts, obtaining a minute of energy expenditure. Reading the entire dataset and adding the results, will give the final EE for the entire set of activities present in the dataset in kj, which is then converted to Kcal. We also add a base metabolic rate (BMR) calculation using the Harris–Benedict equation (13) and (14) to ensure resting values are above the BMR.

$$Women: BMR = 655 + (9.6 * weight(Kg)) + \left(1.8 * height(Cm)\right) - (4.7 * \text{age(Years)}) \quad (13)$$

$$\text{Men: BMR} = 66 + (13.7 * \text{weight(Kg)}) + (5 * \text{height(Cm)}) - (6.8 * \text{age(Years)}) \quad (14)$$

Making use of the linear algorithm, the parameters a_L, b_L and BMR are calculated. The dataset is then read, in order to calculate the horizontal magnitude $H(k)$, defined by the square root of the sum of the squared Y and Z axes for each sample, and the vertical magnitude $V(k)$, defined by the square root of the sum of the squared X axis. We then calculate the average result for each minute of samples by reading the timestamp value in each dataset, estimating EE for each minute using the linear equation.
The applied equations to estimate EE only accepts accelerometer counts, which is proprietary measurement [59], while the smartphone collected datasets are composed by raw accelerometer values. To obtain a reliable estimation, accelerometer raw values need to be converted to the corresponding value in counts. Accelerometer counts start at zero and have an undefined max value. To match the lower bound of zero, each sample is low pass filtered, in order to reduce spikes, smooth data and remove gravity. Gravity is removed in order to report an acceleration of zero on the vertical axis while standing still, matching the lower bound of accelerometer counts and only reporting the acceleration of the subject.
Since no means of reliable and accurate EE calculation were possible, like DLW or indirect calorimeter, an estimation was calculated using the metabolic equivalent of task (MET). MET

acts as a guideline for intensity, but can also be used to estimate energy expenditure. Using the MET reference activity value as provided by the MET guidelines (see Table 1) and the user weight, a fairly accurate estimation of EE can be obtained (15).

$$\frac{MET * 3.5 * weight(Kg)}{200} = Kcal/minute \quad \text{(15) [60]}$$

Algorithm development and EE estimations were performed on subject 1 (see Table 15), who collected running, walking and resting activities. The resting EE was obtained by calculating one MET, resulting in resting energy expenditure per minute of 1.225Kcal. To estimate the energy expenditure for the running activity (see Table 7), the time and distance was used to calculated the speed, therefore allowing the estimation of maximal oxygen consumption (VO2) and estimate a MET value from it, since MET expresses the energy cost in VO2, and is set by convention to 3.5 ml/kg/min for a MET value of one.

In dataset 1, the speed in Km/hour is calculated by doing $\frac{(60(\mathrm{min}) * 5(\mathrm{km}))}{24(\mathrm{min})} = 12.5\ \mathrm{km/h}$. The speed calculated is then converted to meters per minute, required for the VO2 equation, resulting in 208 meters/minute. Using the VO2 equation for running (16) [61] and the previously calculated values, a VO2 value of 41.6 ml/kg/min is obtained which is then divided by the base MET value of 3.5 ml/kg/min to obtain a MET value of 11.88.

With the MET value calculated, we can now estimate EE, obtaining $\frac{(11.88\mathrm{MET}'\mathrm{s} * 3.5 * 70\mathrm{Kg})}{200} = 14.45\ \mathrm{Kcal/minute}$ (15), and since our running activity in dataset 1 has a duration of 24 minutes, a final estimation of 346.92 Kcal was obtained.

$$(meters/minute * 0.2) + (meters/minute * inclination(decimal) * 0.9) \quad \text{(16)}$$

Table 15. Main subject used for algorithm development

Subject #	Sex	Weight (Kg)	Height (Cm)
1	Male	70	173

Having obtained an estimation of EE for accelerometry raw values, the upper bound of accelerometer counts can now be estimated. To obtain this, we propose the following method. Each axis from the raw accelerometry values are multiplied by themselves and by two different offsets, one for the horizontal axes and another for the vertical axis. This allows a more precise adjustment of these values, since these are independent in the EE equations used. These offsets are adjusted in order to increase and adjust the final values as needed (see Table 16 until a EE value close to the previously estimated is obtained.

Table 16. Proposed raw accelerometer values to accelerometer counts adaptation

```
public void addValue(float[] sensorValues) {
float[] filterValues = lowPass(sensorValues);
        nValues++;
        double hOffset = 5;
        double vOffset = 2.2;
        double hValue = (filterValues[1] * vOffset - filterValues[1] / hOffset);
        double hValue2 = (filterValues[2] * vOffset - filterValues[2] / hOffset);
        double vValue = (filterValues[0] * vOffset - filterValues[0] / vOffset);
        sensorSumHorizontal = sensorSumHorizontal + (Math.sqrt(Math.pow(filterValues[1] *
hValue, 2) + Math.pow(filterValues[2] * hValue2, 2)));
sensorSumGravity = sensorSumGravity + filterValues[0] * vValue;
}
```

After adjusting the raw accelerometry values through the proposed method, EE was estimated with a high correlation to the reference values (see Table 17). The linear model underestimates EE for resting and exercise activities.

The non-linear expression (5) was also tested using the same datasets and the proposed method of converting accelerometer raw values to counts. This introduces a new set of parameters: a_N, b_N, P1 and P2 that were calculated for each subject. The results demonstrate a low correlation with the reference values (see Table 17), underestimating EE for both resting and exercise activities.

Table 17. Algorithm results against reference values for dataset 1 and 2.

Experiment	Dataset	Linear algorithm estimation (Kcal)	Non-linear algorithm estimation (Kcal)
1	1: 24 minutes activity and 24 minutes resting	**395kcal**	223.8kcal
2	2: 52 minutes resting	**84.9kcal**	4.8kcal

Energy expenditure was also estimated for some subjects of the physical education class accelerometry datasets (see Table 18). Due to the variety of activities performed, estimating EE with accuracy for all subjects is difficult without a reliable method. To measure the accuracy of the algorithm, the energy expenditure was estimated by assigning a MET value to the performed activities. A value of 6 MET's was chosen, representing medium intensity (see Table 1), after observing the students in the physical education class during accelerometry data collection. An average correlation was observed between the estimated EE using MET and the linear algorithm implementation. An underestimation of EE was observed for subjects 4, 5 and 6. In Table 18 the obtained results can be observed and compared to the reference calculated values. This table also contains the subject's weight, which is a relevant feature for EE estimation. A chart with all experiments can be observed in Figure 22.

Table 18. EE estimation against student's reference values

Subject #	Weight (Kg)	Time (minutes)	Sex	Algorithm estimation (Linear) (Kcal)	Non-linear algorithm estimation (Kcal)	MET estimation (Kcal)
3	45	79	Female	455 Kcal	**330.58 Kcal**	4.725 * 79 = 373.2 Kcal
4	62	76	Male	**456 Kcal**	360.71 Kcal	6.51 * 76 = 494.76 Kcal
5	65	62	Female	430 Kcal	211.80 Kcal	6.85 * 76 = 520.6 Kcal
6	57	80	Male	342 Kcal	298.60 Kcal	5.98 * 80 = 478.8 Kcal

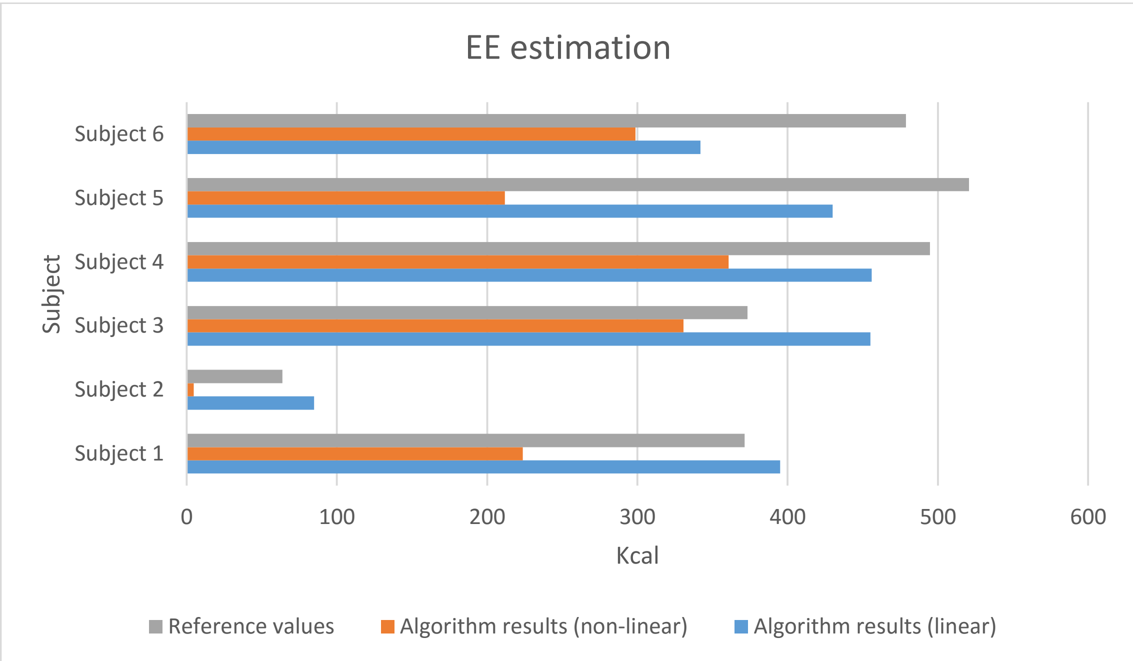

Figure 22 - Chart comparison of all EE estimations.

The obtained results regarding EE estimations for both algorithms prove that the linear algorithm better estimates energy expenditure, with the exception of the results for subject 3, in which the linear expression overestimates the prediction, and the non-linear gets closer to the reference value.

The performed experiments were motivated by the importance of having a representation of actual energy expenditure in the proposed assessment tool. EE is an important measurement, since it will allow a better understanding of the total energy requirements by students, allowing them to balance the energy derived from food with the expended in physical activity, preventing obesity and other diseases like diabetes. It is also important nowadays that people have some kind of knowledge regarding this type of information, allowing them to make better decisions regarding food choices and physical activity levels. For this reason, children should be instructed from early on about the meaning of these terms.

6.3. Activity recognition

Activity recognition was performed using a subset of the classifiers available in Weka version 3.8.0. Weka is a collection of learning algorithms for data mining tasks, containing several other tools for data pre-processing, classification, regression, clustering, association rules, and visualization.

Based on previous studies, the classifiers tested were Multilayer Perceptron, since in Akram Bayat et al.[15] it classified activities both in pocket and in hand with great accuracy, and KNN, since in Wanmin et al [16] it had good performance in walking and jogging activities. We also test Naive Bayes, J48 and SVM which are popular classifiers, and ZeroR to determine the baseline performance. Classifier combination will also be teste based on good results in Akram Bayat et al.[15].

Table 19. Classifiers used

J48 - Decision trees
Multilayer Perceptron (MP or MLP)
IBK (KNN) - K-nearest neighbour
Naive Bayes
ZeroR
SVM (SMO) – Support vector machine

We performed a first experiment using dataset 1 (see Table 7) using different classifiers. We started by preprocessing the data in Microsoft Excel, since it allows a quick way of editing multiple lines of a single dataset. We removed the first and last seconds of activity, which contain only the movement of placing or removing the device from the smartphone bag. We also annotated each instance with the corresponding activity, using the periods identified by the timestamp (see Table 8).

For feature extraction, VBScript was used in Microsoft Excel to extract relevant information to help identify activities present in this dataset. Features were calculated for a window of samples of variable size. Feature selection include the mean for the X, Y and Z axes, the standard deviation for X, Y and Z axes, the magnitude of all axes combined, the minimum and maximum magnitude for the specified window size, and the minimum and maximum value for each X, Y and Z axes. This particular choice of features is based on the current literature [16].

We tested a window size of 1, 5 and 10 seconds. The literature identifies different optimal window sizes ranging from 1 to 10 seconds. These window sizes must be adapted to the activities to identify, since they should capture at least an entire performed activity pattern.

Table 20. Features extracted

Mean for each axis
Standard deviation for each axis
Magnitude of all axes combined
Minimum and maximum magnitude for all axes combined
Minimum and maximum for all axes

We used a 10-fold cross-validation for all classifiers to avoid overfitting. The data is randomly divided into ten equal buckets, with each bucket being used as a test set and training done on 90% of the data. In the end, the results are averaged over the ten cases. All classifiers settings were left at default values.

Using a one second window size, a baseline performance is identified by using the ZeroR classifier, to obtain a base reference classification accuracy. ZeroR is a simple classification method. It ignores all predictors, always outputting the majority class, which in dataset 1 is the resting activity. An overall accuracy of 41.8% was achieved.

Using J48 decision trees, a regression model is built in the form of a tree structure composed of rules. It breaks down a dataset into smaller subsets, with the top node called root node, and being the best predictor. An overall accuracy of 93.36% was achieved with the root node being the mean of the horizontal Y axes.

KNN stores all available cases and classifies based on a similarity measure. Classification is done based on majority voting of the k-nearest neighbors and is measured by a distance function. It was the classifier that took more time to complete, but also one of the ones that achieve better results, with an overall accuracy of 91.92%.

Naive Bayes is a very simple and fast classifier, which is useful for big datasets. It is based on the Bayes' theorem, which describes the probability of an event, based on conditions relevant to it. An overall classification accuracy of 90.16% was achieved.

Multilayer Perceptron is an artificial neural network model that maps inputs to outputs, using a supervised learning technique called backpropagation for training. It is based on the neural structure of the brain, learning from experience. It was the best performing classifier in Akram Bayat et al.[15]. An overall accuracy of 92.46% was achieved for dataset 1.

Support vector machine (SVM) is a supervised learning method with associated learning algorithms for pattern recognition. It achieved an accuracy of 90.13%.

The best single overall classifier, with a window size of 1 second is J48, with an accuracy of 93.36%. For individual activities, the best classifier for walking recognition was J48 with 85.9%

accuracy. For running, J48 was also the best with a 92.1% accuracy result. For resting, all classifiers performed very well, with accuracies above 90%, with the best performer being J48 (see Table 22).

Combining classifiers may improve accuracy over single classifiers as seen in Akram Bayat et al.[15]. Classifier combination was used through Weka's Vote Class, allowing the combination of classifiers using several methods like the average and product of probabilities, minimum and maximum probability, majority voting and median. The used voting rule was the average of probabilities, since in the literature it provided the best results. This algorithm calculates the average probability for the chosen algorithms to combine, and selects the class with most occurrences. Each classifier has the same contribution to the final prediction.

Combining J48 and MP yielded a classification of 93.17% accuracy, achieving second place overall. In individual activity recognition, classifier combination couldn't achieve better results than J48 on any activity.

The overall accuracy results can be seen on Table 21. On Table 22, the individual classification for each activity, using the F-measure of each classifier is listed. The F-measure considers both the precision and the recall of the classification.

Table 21. Overall accuracy for 1 second window size

J48+MP	J48	MP	KNN	Bayes	SVM
93.17%	**93.36%**	92.46%	91.92%	90.16%	90.16%

Table 22. F-measure for a 1 second window size

Activity	J48+MP	J48	MP	KNN	Bayes	SVM
A1. Walking	85.4%	**85.9%**	84.5%	83.5%	79.1%	78.8%
A2. Running	92.0%	**92.1%**	91.2%	89.9%	**92.1%**	**92.1%**
A3. Resting	98.4%	**98.5%**	98.1%	98.4%	94.8%	94.8%

Using a 5 second window increased individual accuracy for activity recognition. The best classifier for walking is KNN with 86.9%. For the running activity, SVM and Naive Bayes are the best classifiers with 92.3%, and for the resting activity, KNN is again the best performer with 98.9%. Overall, we can consider that increasing the window size to 5 seconds improved recognition on all classifiers, improving the recognition of all individual activities over a 1 second window length.

Table 23. Overall accuracy for a 5 seconds window size

MP + KNN	J48	MP	KNN	Bayes	SVM
92.85%	90.99%	92.39%	**93.16%**	90.37%	90.06%

Table 24. F-measure for a 5 seconds window size

Activity	MP + KNN	J48	MP	KNN	Bayes	SVM
A1. Walking	85.7%	80.8%	84.7%	**86.9%**	79.7%	78.8%
A2. Running	91.2%	90.2%	92.0%	91.2%	**92.3%**	**92.3%**
A3. Resting	98.5%	97.4%	97.2%	**98.9%**	94.8%	94.5%

With a window size of 10 seconds, all classifiers performed worse except SVM. The best overall classification result obtained was of 91.61% for the MLP classifier. Bigger window sizes will not adapt well to the patterns in the activities involved, resulting in a decline in classification accuracy. Combining the best classifiers (MP and KNN) resulted in a classification accuracy of 90.68%, which is still below single classification using MLP classifier.

Table 25. Overall accuracy for a 10 second window size

MP + KNN	J48	MP	KNN	Bayes	SVM
90.68%	88.50%	**91.61%**	90.37%	90.06%	90.37%

Table 26. F-measure for a 10 seconds window size

Activity	MLP + KNN	J48	MP	KNN	Bayes	SVM
A1. Walking	82.4%	76.7%	**83.3%**	81.7%	79.2%	79.5%
A2. Running	87.9%	87.6%	90.5%	87.9%	**92.2%**	**92.2%**
A3. Resting	**98.1%**	96.3%	97.4%	97.8%	94.5%	96.3%

A window overlap has been shown to improve activity recognition in the literature [14]. We applied a window overlap of 50% to our best result window (5 seconds), resulting in a 2.5 second window overlap. Results demonstrated no improvement in activity recognition for these particular set of activities.

Table 27. Overall accuracy for with a 5 second window size and 50% overlap

MP + KNN	J48	MP	KNN	Bayes	SVM
92.30%	**92.30%**	92.77%	91.92%	90.05%	89.89%

Table 28. F-measure for a 5 seconds window size and 50% overlap

Activity	MP + KNN	J48	MP	KNN	Bayes	SVM
A1. Walking	**84.1%**	83.0%	83.8%	83.5%	78.7%	78.1%
A2. Running	91.8%	**91.9%**	91.5%	90.0%	**91.9%**	91.7%
A3. Resting	97.5%	97.3%	97.5%	**98.3%**	94.8%	94.8%

The best results are achieved using a windows size of 5 seconds, without overlapping windows. The best classifiers identified using the previous setup are KNN for walking, with 86.9% accuracy, SVM and Naive Bayes for the running activity, with 92.3% accuracy, and for the resting activity KNN is again the best performer with 98.9% (see Table 29).

Table 29. Best classification achieved for each activity

A1. Walking	KNN (86.9%)
A2. Running	SVM and Naive Bayes (92.3%)
A3. Resting	KNN (98.9%)

The activities present in this dataset were successfully identified, with some lower results for the walking recognition. The data pre-processing is very important to identify the activities for each instance. In this dataset, activities were identified based on the performed time, which might be slightly inaccurate and may influence the final classification results. The resting activity recognition results were very good, since this activity is very easy to distinguish from the others due to its small acceleration values.
The best classifiers identified in the literature were used, along with several window sizes to identify activities in the school accelerometry dataset. A window size of 5, 10, 30 and 60 seconds was tested, with the best results achieved using a 5 second window size.
Using a 5 second window and the combination of features in Table 30 produced the best results (see Table 31). The best overall classification result was achieved using a combination of classifiers through the average of probabilities, with an accuracy of 49.37%.

Table 30. Features used in classification of the school accelerometry dataset

Mean for each axis
Standard deviation for each axis
Magnitude of all axes combined
Minimum and maximum magnitude for all axes combined

Table 31. Best classification and classifier for each activity of the school accelerometry dataset

A1. Running	88.4% (KNN)
A2. Volley	60.9% (SVM+MP)
A3. Handball	37.6% (J48)
A3. Basketball	52.8% (SVM+MP)
A4. Futsal	46.9% (MP)

The resulting classification results proved that these activities are harder to identify, with the best accuracy in the running activity classification, due to its linearity. Other activities according to our observations contained too many resemblances in student's movements among the performed activities in physical education class, possibly being the cause behind the low classification results.

6.4. Remarks

Activity recognition using accelerometry or any other sensor data, is an area of active research (e.g. literature [12–16]). The literature provides a valuable set of methodologies and techniques that these classification experiments were based on. For activity recognition, several important aspects were identified, like the best number of samples per second of accelerometry data to collect, the features to extract from the dataset, the best window size, the best single classifiers, and other techniques that can improve results such as window overlap and combination of classifiers. All these aspects were adapted to our datasets and activities performed in order to optimize the classification result. These experiments were meant to assess the effectiveness of accelerometry data in activity recognition and produced good results for linear activities like running, but average results for the more complex ones, since many movement similarities are present. This classification could probability achieve better results if the classified activities were performed with greater technique, e.g. if performed by professional athletes.

Activity recognition can be used to automatically identify the activities performed by students, delivering a more detailed set of information to improve the proposed assessment solution.

For EE estimation, the equations developed in K. Y. Chen et al [9], provide a quick and reliable method of calorie estimation using only basic user information like weight, height, age and sex, combined with the accelerometry values for each minute of activity. The accelerometry raw values required an adaptation prior to usage, since these equations are meant to use accelerometer counts. An algorithm was proposed to adapt these values, matching the lower bound by removing the gravity, and the upper bound, by multiplying the raw values by an adjustable offset until a reference value for EE was reached. Since no precise means of EE estimation was possible, such as DLW or indirect calorimeter, a reference value was estimated using the MET, VO2 and subject weight. The implemented algorithm demonstrated good results for linear activities like running, walking and resting and produced average results for a more complex set of activities.

7. Conclusion and Future Work

7.1. Major Conclusions

The goal of the work here presented, is the building of a solution to complement the student's assessment process, providing the teacher with accelerometry extracted information for decision support in the grading system, and motivating students to pursue more active lifestyles, ultimately fighting obesity and other diseases like diabetes. The developed solution is composed of a complete set of tools, to collect, extract and present activity related information from accelerometry. These analysis tools provide support in the evaluation process, introducing innovation to the assessment system, through the generation of various graphs containing the subject's acceleration magnitudes, steps, path and a new proposed metric called REA. This metric was developed due to the heterogeneity of devices used for accelerometry data collection, producing useful results for student comparison, but requiring a great deal of familiarity regarding the student's physical capacity, in order to determine if he is performing at his best in order to guarantee a correct calibration. The presented information allows the teacher to accurately monitor at any time, the student's activity evolution in the physical education classes.

Various experiments were performed to assess accelerometry effectiveness in a variety of information extraction. EE estimation demonstrated good results for a particular set of activities against estimated reference values, with the best estimations being performed on linear activities like running, walking and resting. For optimal comparison and algorithm development, a reliable method like DLW or indirect calorimeter is needed. Activity recognition using accelerometry data, identified linear activities with good accuracy proving that accelerometry alone can be used to predict activities, but for the physical education class environment, improvements are still required in order to correctly identify the variety of activities performed.

In the implemented prototype for accelerometry data collection, students demonstrated interest in the experiment, requesting access to the extracted information. The extracted information from the collected accelerometry data, namely the various magnitudes, number of steps, path, REA and EE, proved to accurately represent each student's activity intensity, and provide a way to visualize each student's evolution.

The accessibility of this solution was regarded as important throughout development. The proposed assessment solution is easy to implement, only requiring a server for the frontend application, to perform data extraction and to store the accelerometry datasets. It is also low-cost, since the student's smartphones can be used for accelerometry data collection, only requiring the purchase of a transportation bag.

With the development of this solution, community contributions were made by providing the school accelerometry dataset collection for free, as well as the mobile client used for data collection along with its source code. Since current research based on sensor data like accelerometry is performed on different datasets, results between different studies can be hard to compare since different sensors and demographic groups are used to capture data on a variety of activities. With the contribution of our datasets, we make available a combination of useful features for future studies, by providing accelerometry data from children of school age, performing in the class environment a set of real-world activities that were naturally executed and collected on a variety of smartphones.

The collected dataset will enable the development of new applications on a public and shared accelerometry library. The developed mobile client provides new means to create new applications in the area of accelerometry, through the development and free distribution of software that enables easy accelerometry data collection and upload. This allows accelerometry sensor data to be easily collected and used for information extraction for use in many different areas. This mobile client was made publicly available in the play store [18], adding the option to use a custom server address for file upload. The source code is also available in GitHub [19] with the GNU GPLv3 license, in order to require code improvement to be made public in the same terms therefore sharing improvements with the community.

7.2. Future Work

The current solution's prototype proved its potential to be used in physical education class as an accurate and reliable means to complement student's assessment. With the implementation of this solution, other functionalities to increase student motivation towards a more active lifestyle can be developed. A gamification approach can be employed, introducing objectives regarding physical activity for each student, like reaching a certain number of steps or achieving a certain total activity intensity during physical education classes. The school may even create an award system for the most active students, the ones who displayed the biggest increase in activity over time, or even create competitions. This kind of approach will encourage the usage of this solution by students and will contribute to the creation of a new and innovative system to fight obesity and motive students to practice a more active lifestyle.

The history of the student's activity can be used as an alarm system to identify student demotivation or other factors that contribute to a decrease in effort or activity intensity, like illness or depression.

In a future implementation, all collected data including the accelerometry datasets, should be encrypted before transmission, using a symmetric key shared through a key exchange protocol like Diffie-Hellman, or using the current implemented RSA public-key mechanism.

The number of samples collected per second by the mobile client can be optimized. In the development of this solution a big number of samples was needed to test and developed the algorithms, resulting in a relatively large file to upload, possibly being the main cause of some data loss. The optimal lower number of necessary samples can be investigated, by testing lower sampling rates until a similar performance is obtained. This will reduce dataset size and improve the algorithm performance by requiring less data to be processed.

The current front end web application used to consult extracted information can be improved by adding functionalities like an administrator section with access to various logs, user control and information management. Allowing comparison of multiple users, or grouping can also implement an improved user comparison by classes, ages and genders.

Activity recognition using accelerometry data was a successful experiment performed, and in a future implementation with an improved classification system, activities can be automatically identified and used to generate individual statistics.

An important aspect of this solution is the usability. Freeing the users of most of the tasks will improve user experience and will encourage them to keep using it. The current solution automates most of the tasks, requiring only the user to start and stop the data collection. A future implementation might schedule data collection, or automatically detect activity and start the collection process.

Smartphones are a common device to implement the mobile client's data collection process, but can be expensive and bulky. With the advent of dedicated fitness trackers, a future solution might make use of data collected by these devices. These devices are low-cost, lightweight and provide accurate accelerometry data. Since a homogeneous set of devices would be available for all students it would also improve the extracted information precision and multiple student comparison. A mobile client will still be required for data upload, but would not be required during the data collection process.

In the future, new prototypes can be implemented in schools, in order to collect feedback and improve the proposed solution.

8. Concluding Remarks

The presented solution enhances common technologies like accelerometer sensors present in smartphones as a way to evaluate physical activity, enabling the development of an innovative assessment system to complement the teacher's evaluation and grading system. The collected datasets enabled the extraction of activity information from a variety of subjects and devices, allowing the development of reliable tools to compare student evolution over time.

This solution includes specific knowledge in REST web services for the implementation of a client-server architecture, being very light on smartphone resources since all major computations are on the server side. Several algorithms were developed to extract information like steps, magnitude, EE, subject's path and REA to generate the analysis tools. A front end single page web application was developed, enabling quick access to the extracted information. User privacy is also guaranteed, since the current implementation encrypts the uploaded user information.

Activity recognition was part of an experiment to assess the effectiveness of accelerometry data in activity recognition. It performed with good accuracy for a simple set of activities. Several classifiers, window sizes and extracted features were compared.

Community contributions were made, providing the mobile client and its source code for free, as well as the collected physical education class dataset composed of 18 students performing several activities.

A new metric called REA was proposed, getting some of its inspiration on the MET measure, motivated by the need to compare subject's information in a highly heterogeneous class environment (not only technological differences in the available equipment's must be considered but also other factors such as anthropometrics, lifestyles, nutrition, and ethnic composition of populations should be accounted for). The main feature chosen to use for evaluating overall activity intensity was the proposed REA measurement, since it combines all the available accelerometry information, allowing a reliable student comparison, assuming that a correctly calibration was performed. We are aware that there are many differences regarding student inherent capabilities, but there is one immediate insight that is possible to obtain by using the proposed measure: it is possible to say how the perceived effort from the movements of any given student in team sport activities relates with the effort spent in a standardized high intensity activity.

The developed work involved many different areas that were required to the building of the final proposed solution. The areas of greater research and most time consuming were the algorithm implementation of energy expenditure, since the lack of a reliable measurement method limited the algorithm's testing and adaptation to raw accelerometry values. Machine learning activity recognition was also a challenge, since each dataset is unique and needs extensive testing with different classifiers, features and window sizes. The information to extract from the accelerometry datasets was also a subject of extensive study and research, ultimately achieving a total of six reliable features regarding physical activity.

Another interesting facet of this solution, at least for an entrepreneur, is that it lays at the foundation of a business model that we are developing. Our value proposition focuses on the innovation, benefits regarding the assessment system, student motivation and low-cost of this solution. The prototype implementation and its success are described, enumerating the benefits and added value that this solution brings to schools and the current physical education assessment system. This business model describes the prototype's successful implementation in a school, the key partners, customers, expenses, revenue, and other relevant aspects like sales channels and key resources.

Sensor data provides great opportunities for the development of new solutions to improve quality of life.

In this regard it is essential to gather as much suggestions for improvement as possible reason why we have submitted a paper to a peer-reviewed international IEEE conference reporting some of the work here presented. Powered by this kind of feedbacks and also by the opinions of the target groups of users we intend to continue the development of this solution to the fullest extent possible.

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Appendices

Appendix A - Physical Education Class Accelerometry Dataset Description

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Physical Education Class Smartphones Accelerometry Data Set

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Jason Costa (1), Paulo Fazendeiro (1), Filipe Ferreira (2)

1 - Universidade da Beira Interior

2 - Agrupamento de Escolas Frei Heitor Pinto

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The experiments have been carried out with a group of 18 volunteers within an age bracket of 13-17 years. Volunteers were divided in two groups (GROUP A and GROUP B) performing the same activities but on different days. Each person performed 5 sports activities (RUNNING, FUTSAL, VOLLEYBALL, BASKETBALL, HANDBALL). The collective sports activities were performed by playing team matches of 4x4, wearing a variety of Android smartphone devices on the waist. Using its embedded accelerometer, we captured 3-axial accelerometry data at the device's max rate. The obtained datasets are divided by subjects and are accompanied by the used smartphone model and the subject's physical information (AGE, HEIGHT, WEIGHT, SEX).

The accelerometry signal was pre-processed by applying a low-pass filter and each sample contains a corresponding timestamp in milliseconds obtained from the smartphone.

For each record it is provided:

======================================

- Triaxial acceleration from the accelerometer (accelerometry).
- A timestamp in milliseconds.

The dataset includes the following files:

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- 'README.txt'
- 'SUBJECT_INFO': Shows information regarding each subject's weight, height, age and sex.
- 'DEVICE_INFO': Shows information regarding each subject's smartphone used for data collection
- 'ACTIVITY_LIST.txt': Shows information about each activity time period and other details.

Notes:

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- Datasets are divided by GROUP A and GROUP B.
- Each sample is saved in a line using the format X;Y;Z;TIMESTAMP.
- Timestamp is saved in milliseconds and is obtained from the smartphone's time.
- The units used for the accelerations (total and body) are 'g's (gravity of earth -> 9.80665 m/seg2).

For more information about this dataset please contact: jasonphilipsardocosta'@' gmail.com

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Jason Costa, Paulo Fazendeiro, Filipe Ferreira. June 2016.

Appendix B – Proposal for an entrepreneurship contest

Figure 23 – Business value proposition.

Figure 24 – Prototype implementation.

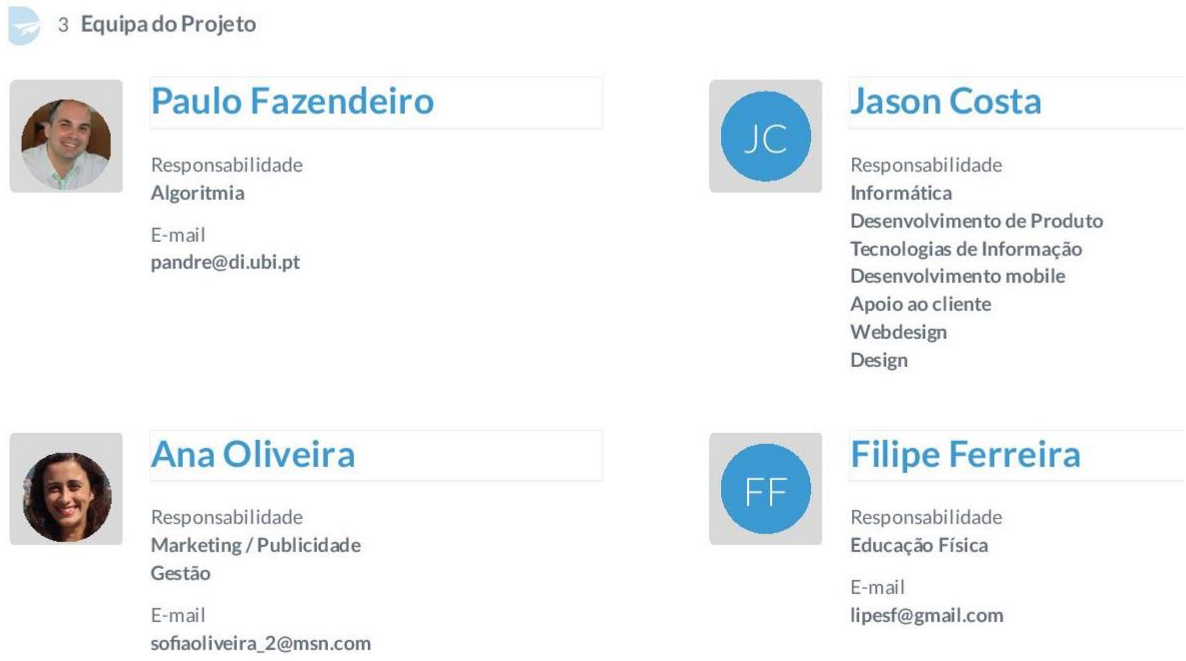

Figure 25 – Team behind the business model and project.

4 Modelo de Negócios

Parceiros Chave

Parceiros: Ministério da educação e escolas; Professores e alunos; Fornecedores de internet; Empresa de alojamento e domínio para o website; Designers; Fornecedores de bolsas de transporte para smartphones; Peritos da área da saúde e desporto; Peritos da área de algoritmia e análise de dados;

Atividades Chave

Atividades: Desenvolvimento de melhorias e funcionalidades; Sugerir funcionalidades ao cliente e fornecer ajuda à sua utilização; Manter um contacto constante com o cliente de forma a recolher feedback; Pesquisa de novos mercados para implementar o produto; Procura de potenciais parceiros e clientes;

Recursos Chave

Recursos: Domínio e espaço de alojamento para o website, assim como computadores com Mac OS e Windows para desenvolvimento IOS , Android e Windows Phone com as respectivas licenças e smartphones para testes. Será também necessário recursos humanos para suporte ao cliente à distância e presencial.

Proposta de Valor

Proposta de Valor: Método inovador de monitorização da evolução da condição física dos alunos nas aulas de educação física, assistindo o docente no processo de avaliação ensino-aprendizagem. Além de objetivar a avaliação, poderá ser utilizado em processos de motivação e de combate ao sedentarismo dos alunos.

Relações com Clientes

Canais de Venda: Através da disponibilização de períodos grátis de teste, sem compromissos, onde poderão comprovar a qualidade e utilidade do produto, assim como a disponibilização de suporte de apoio constante à resolução de problemas e ajuda na utilização.

Canais

Canais de Venda: Através do contacto direto com o ministério da educação, instituições de ensino e outras organizações de áreas como desporto, saúde e educação.

Clientes

Clientes: Instituições de ensino públicas e privadas que procuram melhorar os seus métodos de avaliação (professores utilizarão uma plataforma para avaliar os seus alunos de uma forma detalhada e fiável por meio de métodos inovadores) e que se preocupam com o bem estar e acompanhamento dos seus alunos.

Despesas

Rúbricas de Custo: Deslocação, Internet, Computadores, Salários, Website, Smartphones para testes, Licensas de software, Publicidade online, Renda, Água e electricidade, Equipamento de escritório
Custos Variáveis: Plataforma base, 1 ano: 6000, 2 anos: 12000, 3 anos: 18000; Módulos com funcionalidades, 1 ano: 0, 2 anos: 0, 3 anos: 0

Receitas

Fontes de Receita: Plataforma base, Módulos
Estimar receitas: Plataforma base (top_line_estimation_types.subscription), 1 ano: 100000, 2 anos: 200000, 3 anos: 400000; Módulos com funcionalidades (top_line_estimation_types.single_sale), 1 ano: 50000, 2 anos: 100000, 3 anos: 200000

Figure 26 – Business model overview.

Figure 27 – Sales channels.

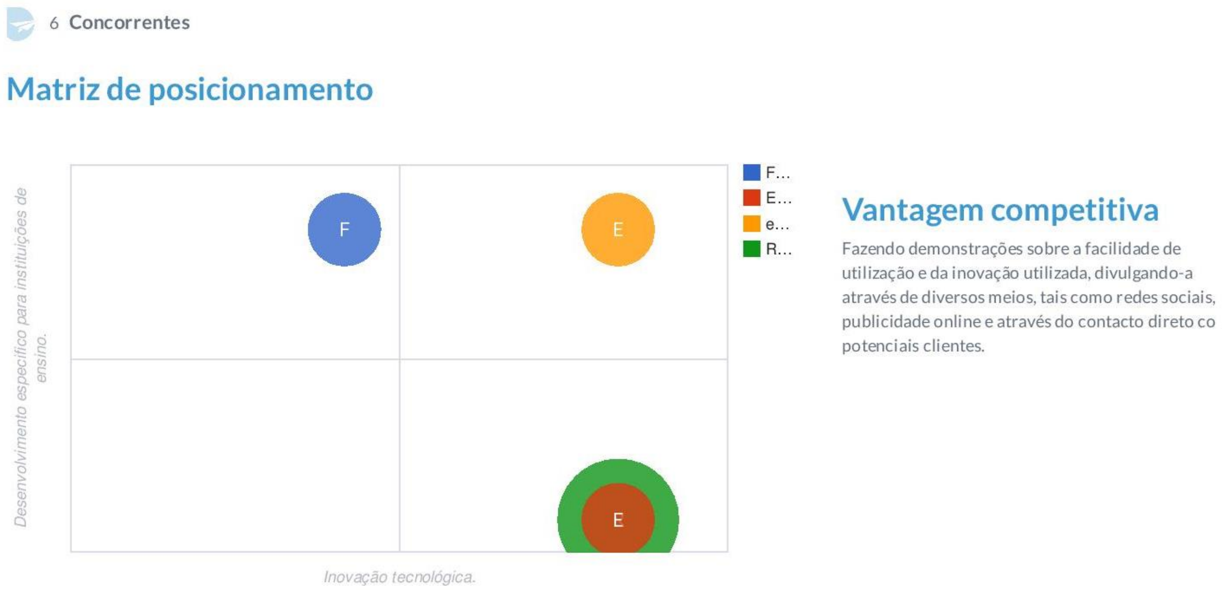

Figure 28 – Competitive advantage.

Figure 29 – Business operations.

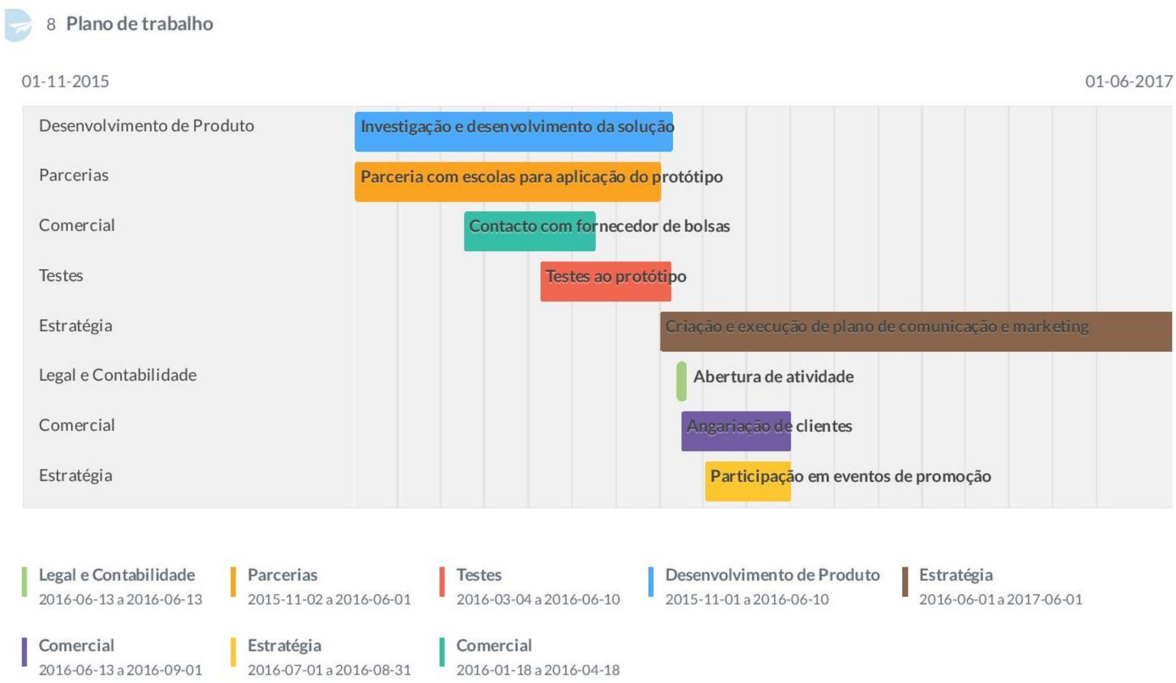

Figure 30 – Developed work strategy.

9 Resultados

	Tempo		
	1 ano	2 anos	3 anos
Receitas	150.000,00 €	300.000,00 €	600.000,00 €
Custos Variáveis	6.000,00 €	12.000,00 €	18.000,00 €
Custos Fixos	61.855,00 €	83.180,00 €	106.380,00 €
Total Custos	67.855,00 €	95.180,00 €	124.380,00 €
Resultado Operacional	82.145,00 €	204.820,00 €	475.620,00 €
Depreciação e Amortização	1.719,31 €	3.055,29 €	4.391,26 €
Resultado Antes de Impostos	80.425,69 €	201.764,71 €	471.228,74 €
Impostos	23.725,58 €	59.520,59 €	139.012,48 €
Resultado Líquido (Lucro)	56.700,11 €	142.244,12 €	332.216,26 €

Figure 31 – Revenue results.

10 Balanços

	Tempo		
	1 ano	2 anos	3 anos
Ativo	63.333,11 €	66.721,80 €	400.990,78 €
Capitais Próprios	63.333,11 €	66.721,80 €	400.990,78 €
Passivo	0,00 €	0,00 €	0,00 €

Figure 32 – Revenue results summary.

11 Métricas de Investimento

	Tempo		
	1 ano	2 anos	3 anos
Fluxos de Caixa	58.419,42 €	145.299,41 €	336.607,52 €
Fluxos Acumulados	58.419,42 €	203.718,83 €	540.326,35 €
Investimento	6.633,00 €	5.108,00 €	5.108,00 €
Financiamento Necessário	6.633,00 €	5.108,00 €	5.108,00 €
Ponto Crítico (Break Even)			0 a 6 meses
Gasto Médio Mensal (Burn Rate)			0,00 € / mês
Total de Investimento			16.849,00 €

Figure 33 – Investment metrics.

Appendix C – Physical education activity list

AULAS - PLANIFICAÇÃO

Aula 2 - Modalidades: Futsal, Andebol, Basquetebol e Voleibol

Dia 23 de maio de 2016

INÍCIO da AULA

a) 0 (tempo de aula) + 10 minutos (tempo gasto)

Equipar e realizar a chamada.

b) (Exercício 1) 10' + 8 minutos + 2 minutos de instrução do próximo exercício

Corrida contínua

Alongamentos

Organização: individualmente realizam corrida contínua seguida de alongamentos.

c) (Exercício 2) 20' + 13 minutos (Voleibol) + 2 minutos de instrução do próximo exercício

Relação EU-BOLA-COLEGA-ADVERSÁRIO-ALVO

Organização: turma dividida em 4 grupos realiza troca de bola tentando que o adversário não fique na sua posse.

d) (Exercício 3) 35' + 13 minutos (Andebol) + 2 minutos de instrução do próximo exercício

Relação EU-BOLA-COLEGA-ADVERSÁRIO- ALVO

Organização: turma dividida em 4 grupos realiza troca de bola tentando que o adversário não fique na sua posse.

e) (Exercício 4) 50' + 13 minutos (Basquetebol) + 2 minutos de instrução do próximo exercício

Relação EU-BOLA-COLEGA-ADVERSÁRIO- ALVO

Organização: turma dividida em 4 grupos realiza troca de bola tentando que o adversário não fique na sua posse.

f) (Exercício 5) 65' + 13 minutos (Futsal) + 2 minutos de instrução do próximo exercício

Relação EU-BOLA-COLEGA-ADVERSÁRIO- ALVO

Organização: turma dividida em 4 grupos realiza troca de bola tentando que o adversário não fique na sua posse.

g) 80' + 10 minutos

Alongamentos e higiene (banho)

FIM DA AULA

Características dos exercícios

Independentemente das modalidades a organização dos exercícios é a mesma para evitar ao máximo a influência das variáveis de contexto. A variável mais influente será a modalidade pois implicará diferentes ações motoras.

Figure 34 – Activity list.