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Assessing the effort of exercise using low cost sensors

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Resumo

No presente trabalho é proposta uma solução que visa ajudar os professores de educação física a fazer a avaliação dos seus alunos, e os alunos a sentirem-se mais motivados com a inclusão de tecnologia nas aulas de educação física e com o facto da métrica apresentada, ser calculada a partir do esforço de cada um, tentando assim ultrapassar alguns vieses inerentes ao processo de avaliação. Foi proposta uma solução que utiliza um sensor, neste caso o acelerómetro, para a obtenção de dados de acelerometria durante a execução de quatro atividades físicas: voleibol, andebol, basquetebol e futsal. Foram recolhidos dados de duas turmas que frequentam o 9º ano. O dispositivo utilizado para a obtenção desses valores de acelerometria foi o smartphone dos alunos, através de uma aplicação móvel que é responsável pela recolha dos dados e por os enviar para um servidor. Esses dados foram sintetizados e analisados de forma a calcular a métrica Running Equivalent of Activity (REA).

Foi realizado um estudo empírico que visa a validação experimental da referida métrica tendo sido testados diversos protocolos experimentais. São sugeridas um conjunto de boas práticas para a adopção da solução ora proposta, no sentido de permitir uma aferição justa e equitativa do esforço aplicado pelos estudantes nas aulas de Educação Física.

Palavras Chave

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

Abstract

In this work, it is proposed a solution that tries to help the physical education teachers in the assessment of their students, also trying to increase the motivational levels of students with the inclusion of new technologies in class, and with the fact that the presented metric, being estimated for each student from their own effort. It is proposed a solution that uses a sensor, in this case an accelerometer, in order to capture accelerometry data during the execution of four physical activities: volleyball, handball, basketball and futsal. Data was retrieved from two classes of the 9th^o Portuguese school year. The device used to capture those accelerometry data was the student's own smartphones, through a mobile application that collects data and sends it to a server. After that data is uploaded, it is analysed in order to calculate the metric Running Equivalent of Activity (REA).

An empiric study was developed aiming at the experimental validation of the metric referred above, having been followed diverse experimental protocols. A set of good practices is suggested for the adoption of the proposed solution, a mean to enable a fair and equitable assessment of the effort applied by the students during the physical education classes.

Keyword

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

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Acronyms

AC	Activity count
ADAS	Actigraph data analysis software
AI	Activity index
API	Application programming interface
BMI	Body mass index
HIRA	High intensity running activity
GPS	Global position system
JAR	Java Archive
MEMS	Micro Electro Mechanical System
MET	Metabolic equivalent of task
OPACH	Objective Physical Activity and Cardiovascular Health
PSG	Polysomnographic
REA	Running equivalent of activity
REE	Resting energy expenditure
SEI	Sleep efficiency index
SOL	Sleep onset latency
V02	Maximal oxygen consumption
WASO	Wake after sleep onset

1. Introduction

1.1. Motivation

Assessment in physical education has many purposes from decision making about classification, diagnosis, and guidance, reporting the progress of a student in developing the knowledge, skills, and attitudes. This assessment has become stagnated, with teachers using the same old methods, and techniques to evaluate their student's overall performance, and grading them according to the national and/or state physical education standards [1]. A physical education teacher grades a student based on four domains: cognitive domain, health-related physical fitness, psychomotor-skills, and effective skills. The cognitive domain is related to the students knowhow, health-related physical is the improvement made by the students regarding fitness levels, and psychomotor-skills is what students are able to perform, and the last domain refers to the attitudes and beliefs about the subject [2].

The teacher needs to collect evidences about the student's performance during the classes and make interpretations about how they progress based on those evidences, which can be demoralizing for some students, that even while trying their best, aren't able to perform as well as some of their colleagues, due to physical limitations or psychological demotivation.

In order to remove these external biases, we propose the use of a metric that could help the teacher assess his students, by comparing the effort of each student in pre-determined activities with their own best effort. The main focus is to motivate the students that may be overweight, or lacking fitness, and at the same time create a more objective student assessment, to help the teacher assess his students.

Schools have a very important role in trying to motivate their students for the practice of physical activities, through the classes dedicated to it, also encouraging them to practice physical activities outside of those classes. These kind of activities are associated with a longer and better quality of life, reducing the risk of a variety of diseases, and introduce many psychological and emotional benefits [3]. For many students, the school is the main environment for physical activities practice through the dedicated classes as well as after-school activities [3].

Schools should have a very important part in raising awareness about important issues like health disorders, they could try to incorporate technology in a way that can motivate the students to put more effort, than they would normally put in a guided physical activity. The physical education classes should be more interactive, allowing the students to check their performance over time. The lack of regular physical activity and bad eating habits may lead to health disorders like obesity, diabetes, cardiovascular diseases, and others. In fact, a 2013 study [4] states that about 13% of the world's population (11% men and 15% women) were obese. High body-mass index (BMI) leads to cardiovascular diseases (heart disease and stroke),

which were the leading cause of death in 2012 [4], and is also related to other diseases like diabetes, musculoskeletal disorders (like osteoarthritis), cancers (endometrial, breast, ovarian, prostate, liver, kidney, colon).

Over the last years, the number of smartphones has substantially increased. In 2016, 2.3 billion people had a smartphone, with numbers expecting to reach 2.6 billion in 2017 [5], [6]. With the increase in smartphones numbers, most children nowadays already possess a smartphone. This device contains many sensors, such as a Global position system (GPS), gyroscopes, accelerometers, temperature, magnetometers, and barometers, and with the help of a mobile application, those accelerometry values can be retrieved in order to analyse them, according to our need.

1.2. Objectives and synthesis of the state of the art

We argue that the use of an accelerometer sensor, and of a specially tailored metric of effort assessment to evaluate the student's performance during the physical education classes, can result in a substantial help complementing the teacher's evaluation of his students. The objective of this metric is to circumvent some of the limitations presented on the traditional evaluation methods, removing some of the subjectivity of the evaluation process, such as student's different physical characteristics and device heterogeneity.

At the same time, it is expected that the motivation levels of the students could raise with the inclusion of technology and a fair metric that compares each student performance with their own best effort, through the execution of a calibration activity (for instance, high intensity running). This may lead to students being more motivated, especially those who can't take advantage of their physical structure, or present lack of fitness.

The accelerometer sensor, must be placed in the waist for motion sensing, due to the fact that the waist is closer from the centre of mass of the human body, and is the most comfortable position during the execution of the physical activities, preventing student discomfort during the physical activities [25-27].

We aim to implement a solution that complements the student's assessment, supporting the teacher during the grading process, and helping the students to get motivation and to put more effort during the physical education classes. The chosen metric will be used as a mean to compare the students' own levels of activity and evolution in class, this way, making the students more confident, not only the ones who can't take advantage of their physical structure, or present lack of fitness, but also the ones who are already fit, but always want to give their best.

1.3. Main contributions

From a practical point of view the major contribution of this work was the development of a prototype application that can be used to remove the relative subjectivity that exists in the

student's assessment during physical education classes, by using the student's smartphone. The accelerometry data was captured and used to extract activity information related to each student, to complement the teacher's assessment and grading system. The idea behind the smartphone's accelerometry was to implement a more objective assessment, in a way that can motivate students who cannot take advantage of their physical structure, due to overweight or lack of physical dexterity.

We hope that with the inclusion of technology, and by providing the students with their own data collections, we can motivate them to practice a more active lifestyle and at the same time improve their efforts during the physical education classes. We also hope to help fight obesity and other diseases by trying to create good habits in the students.

An accelerometry dataset was collected from all the students, composed of a set of activities performed during the physical education classes.

A metric of effort called REA (running equivalent of activity) was validated during the execution of four physical activities, using three different approaches that were compared. Student's performance can be analysed and compared by the teacher or by the students, (can only check their own performance) on the front-end application in a graphical way. These charts can be useful to help the teacher's assessing his students and help motivate the students in order for them to put more effort during the physical education classes.

1.4. Organization of this document

This dissertation is divided into 5 sections. In section 2, a brief literature review is made comprising subjects like accelerometers, techniques to capture accelerometry data, the best locations to place the sensor in the body to be unobtrusive to the human body motion, the traditional assessment used to evaluate the students during the physical education classes. Then we proceed to explain the concept of data reduction and some techniques that can be used such as compression or data deduplication. Section 2 also elaborates on some metrics that can be used to assess the effort during physical activities. Section 3 details some of the elements of the system architecture, from the mobile client that needs to be installed on the student's smartphone, the data model, the registry, and login systems and finally the teachers and students web view (on the front-end application). Section 4 details the analysis of the collected accelerometry data, such as the three approaches that were used to calculate the metric. Section 5 provides a summary of the main conclusion about the work that was developed during this time and points to some future work, and provides some personal concluding remarks, discussing the work and the biggest challenges that appeared during its development.

2. State of the art

2.1. Introduction

This chapter discusses the available literature for related areas of this work. First, a brief explanation about how the physical education assessment is being made, proceeding to an explanation about accelerometry, giving examples of its purpose and different areas of application, as well as the available devices with an accelerometer that could possibly be used to capture accelerometry data. Proceeding then to the available locations on the human body where a sensor can be placed. The last two subsections are dedicated to the study of metrics that can be used to measure student's assessment effort, namely the metric that will be used during this study, and the techniques to accomplish reduction of accelerometry data. This will allow for a better understanding of the following chapters.

2.2. Physical Education assessment

Assessment in physical education serves many purposes and contributes to decision making about classification, diagnosis and guidance, motivation, reporting information about a student's progress and achievement in developing knowledge, skills and attitudes [8], [9].

The goals of physical education are to improve physical fitness, sport and rhythmic skills for recreation and daily movement tasks, perform efficient, creative and expressive with an active living lifestyle, demonstrate critical thinking, assess attitudes and behaviours [8]. Often physical education classes have few time allocated in schools, which makes the assessment process not effective as an outcome [10].

Grading is the process of assigning marks to students based on a formal assessment of changes in student behaviour, it increases the students interest, motivation and assesses the effectiveness of instruction [11].

Student assessment is the process of gathering the evidences about student's achievements such as, skills, attitudes, behaviour of learners, and make interpretations about how was the students' progress based on those evidences. A physical education teacher, collects and keeps track of assessment data to make decisions about instructions and to measure student's learning recurrently during the learning process [1], [8].

Physical educators assess based on four domains, cognitive domain, health-related physical fitness, psychomotor-skills, and affective skills. Cognitive domain is what the students need to know (knowhow), health-related physical fitness retracts the improvements made regarding fitness levels, psychomotor-skills is what students are able to do/perform, and the affective domain refers to the attitudes and beliefs about the subject [2].

The use of factors such as attitude, attendance and effort combined with subjective ratings of the student's motor performance, forms the way the actual model uses today in physical education evaluation [12]. Sport skill is possibly the most difficult human motor performance to assess, due to several facts such as complexity of sport performance, appropriateness of existing sport skill tests, and the fact that they need too much time to set up and manage [13]. There are two types of assessments that can be used to evaluate student achievement/progression in physical education [2]. Firstly, formative assessment which is a continuously process made throughout a physical education curricular year, where teachers need to create an inclusive program that meets the needs of the students, lastly, the summative assessment in which the teacher creates a summative physical education task which allows the students the demonstration of specific key skills they have been working on, and the teacher will assess the students based on a series of performance criteria [14], such as shooting position during basketball, or futsal (for example).

Students receive immediate feedback during the classes, with skills being attempted and the participant knowing the result immediately due to direct observation, the problem lies in defining success. If physical education is to be considered an important discipline, then the assessment needs to follow best practice like formalism and timely teacher feedback [15].

To provide a comprehensive summary of each student's progress, the professor needs to conduct pre-assessments to understand at which point the students are at the beginning of a learning sequence, and formative assessments that allow him to track the ongoing instructions. Suitable assessments provide concrete evidence of whether the students have achieved a grade-level outcome, demonstrating that students are meeting the standards and results [2].

In order to complement the assessment of students during the physical education classes, in this work it is proposed a solution that uses an accelerometer and an assessment metric, to help the professor assess his students, at least in the psychomotor skill aspect with the reduction of issues such as subjectivity, device heterogeneity and student's different physical characteristics, allowing a fair comparison between students despite the fitness of each student.

2.3. Assessment equipment and devices

An accelerometer is an integrated electronic component, used to measure acceleration forces exercised on an object. These forces can be static, like a constant force of gravity, or they can be dynamic, caused by movement or vibration of the accelerometer. When the static force is measured, it is possible to find the inclination angle of the device in relation to the earth, and when the dynamic force is measured, it is possible to analyse the kind of movement exercised on a particular object [8-9].

There are various types of accelerometers, each one with their own characteristics, advantages and drawbacks. Accelerometers are divided in two major groups: mechanical and electronic. In the mechanical group the most used are the capacitive, piezoelectric and piezoresistive,

while in the second group, there is the Micro Electro Mechanical System also known as MEMS, this one with a big growth [9-10].

The sensors MEMS are simple devices that emulate the mechanical parts through micro-machining technology and consists, of a cantilever beam with a proof mass and a capping to ensure the degradation by water, dust and physical contact doesn't damage the chip. The inertial force will make the proof mass to deflect when there is acceleration or gravity [7].

The three-axis accelerometer signal can be described using the following formula.

$$a_m = \frac{1}{m} (F - F_g) \quad (1)$$

Where, a_m is the measured acceleration, m is the mass of the body, F is the sum of all forces on the body, and F_g is the gravity force which is $9,81 \text{ m/s}^2$, which is also detected by the sensor [16].

This MEMS device is the one integrated in smartphones, because of his small size, low consumptions, and low costs. Thanks to these factors this type of accelerometer has a huge commercial potential, and enables the development of applications for different areas, medical [9-10], navigation [11-12] and sports [13-14] for instance.

In smartphones, the default position of the accelerometer is in the centre of mass of the device and usually uses a 3-axis coordinate system, as displayed in Figure 1. If it is kept in the default orientation, the x-axis is horizontal and points to the right, the y-axis is vertical and points upwards and the z-axis is perpendicular to the screen.

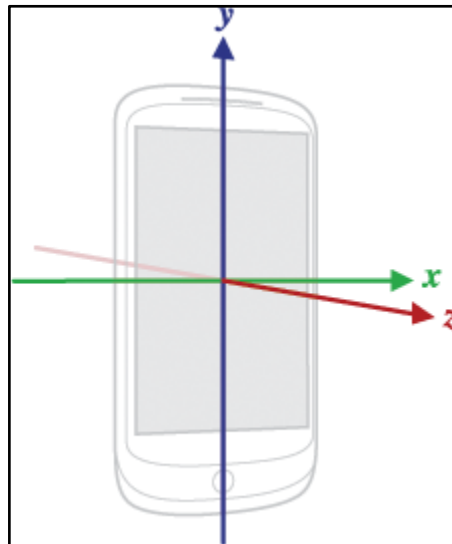


Figure 1 - 3-axis coordinate system in a smartphone [25].

Due to the small size, low consumptions, and low costs, there are a lot of devices with an incorporated accelerometer, like smartphones, pedometers, tablets, smart fitness watches, fitness wristband, activity trackers.

For example, the Fitbit:ZIP, is an external device that has an accelerometer with 3-axis, with the objective of measuring the movements patterns of each user. Allows users to track steps, distances and calories burned [26]. This device can be synchronized with smartphones and computers, in order to keep updated information in real time. Unfortunately, all the Fitbit trackers software are exclusive and not open for developers to work with the device accelerometer values. Another example is the Nike+FuelBand [27], an activity meter used in the wrist, it allows users to see the steps performed and the number of calories burned through an accelerometer. The device can also be synchronized with the application and allows users to track their progress in the smartphone, unfortunately it isn't also open source. Actigraph is a company that traditionally develops high end activity monitors present in several studies. One of their most recent devices the Actigraph GT9X Link [28], includes a gyroscope, magnetometer, and secondary accelerometer to deliver valuable information about movement, rotation, and body position. It captures and records high resolution raw acceleration data, which can then be transformed in a diversity of objective activity and sleep measures. It has measures like raw acceleration (G's), physical activity intensity, activity bouts, energy expenditure, MET rates and others. The main problem of this device it seems to be the high price.

Due to the limitations mentioned before and availability of the accelerometer axis values from almost all those devices, we decided to use smartphones to perform this study, this way it would only be needed a mobile application in order to capture those accelerometry values and no additional equipment has to be purchased.

2.4. Sensor Placement

Sensors can be placed in multiple locations (see Figure 2), on the human body whose movements are being studied, and they need to be unobtrusive to the human body motion [7].

To measure the whole-body movement, the sensor is normally placed on the sternum [29], lower back [30], and waist [31]. Some studies [32]-[34] adopted placing the sensor in the waist for motion sensor, since the waist is closer to the centre of mass of the human body, and being the most comfortable during the activities performance. Since motion will be analysed, and with the information provided by the mentioned studies, in this developed solution the students will place their smartphones on a waist bag provided by us.

Sensors can easily be attached and detached from a waist bag, causing less constraint in body movement, and minimizing discomfort as well. The sensor needs to be securely fitted and attached to the human body, to prevent relative motion between the sensors and the parts of the human body. If the attachment is loose or unsecured, it causes vibration and displacement

of the wearable systems, producing unnecessary signal artefacts and degradation of the sensing accuracy [7].

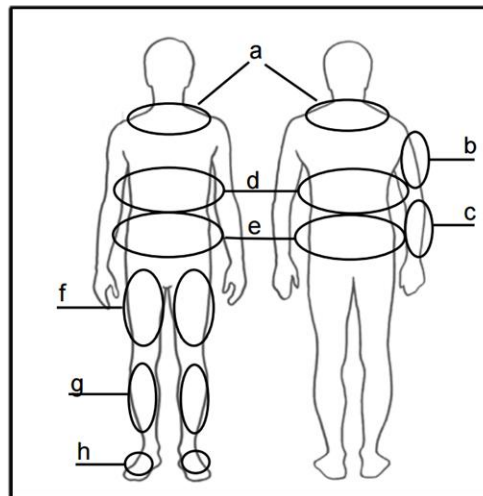


Figure 2 - Sensor Placement locations are: (a) collar area, (b) rear of the upper arm, (c) forearm, (d) front and rear sides of ribcage, (e) waist and hips, (f) thighs, (g) shin, and on (h) top of the foot [35].

2.5. Metrics of effort assessment

Since all students have different physical features, and their accelerometry data can be collected by different devices, a measurement that can be used is the metabolic equivalent task (MET) [36]. This MET is an extensively used physiological concept that characterises a simple procedure for expressing energy cost of physical activities as multiples of resting metabolic rate, allowing us to quantify the energy cost of activities at rest, or the average resting oxygen consumed by the body at rest. One MET represents the energy expenditure at rest (REE) or the resting O_2 consumption (VO_2) [36]. To calculate the MET value, it is necessary to multiply the energy cost of a physical activity by the REE value. MET can be seen as an index of the activities intensities (see Table 1), in a way that people with different weights and heights can be compared [36].

Table 1. Standard MET guidelines for the activities performed by students.

Activity	Met value
Resting	1
Running	12,9 - 14,6
Volleyball	6
Handball	8 - 12
Basketball	11,1
Football	10,3

Another measurement that can be used is the running equivalent of activity, hereafter called REA and expressed as follows,

$$REA_{ACT} = \frac{avgMagn(Activity)}{avgMagn(RunHigh)} \quad (2)$$

This measurement provides a comparison base with other kinds of activities, being defined as the ratio of the standard average acceleration vector of the activity by the previously calculated average magnitude of a calibration activity [37]. For this calibration, it can be used, for instance the high intensity running activity. From hereafter, this activity will be called high intensity running activity (HIRA), and in this work will be used as the base measurement due to the fact that this activity provides consistent accelerometry values [37].

It is important that the students perform the HIRA at maximum intensity without breaks, because all the subsequent activity estimations will depend on this data.

The average of the magnitude (3) for a short period and a high intensity activity, is extracted individually for each student, defining this way the base measurement.

$$mag_{axis} = \sqrt{A_x^2 + A_y^2 + A_z^2} \quad (3)$$

By using this method, the student's comparison is conceivable, without having to worry about their different physical characteristics.

Students collect accelerometry data while running for 2 minutes at their highest intensity, then after this data is collected, it is necessary to calculate the average magnitude for those 2 minutes, providing the base magnitude value for a normalized REA value of 1 [37]. It is also necessary to remove the gravity by using a low pass filter [25], in order to only extract the acceleration of the student, if the gravity were not removed, a vertical acceleration force would be incorrectly reported when students would be standing without moving.

This activity needs to be of short duration, to guarantee that the students run at high intensity, to get a precise representation of the student's maximum performance, if they do not perform this activity at their maximum level, the other activities may report a high magnitude, which will not represent the true activity level. The HIRA value is calculated by identifying the activity by the timestamps presented in the dataset and by calculating the average of the magnitude for all the axis (X, Y, Z) in the defined time. This REA calculation allows an estimation of a related activity measurement, removing the heterogeneity of the different devices used by the students during the collections, allowing this way a more reliable student comparison. REA is calculated for each activity performed, this way, allowing the teacher to check the performance of his students by activity or by an overview of all the performed activities.

This metric had some inspiration on the metabolic equivalent of task (MET), due to the fact that it also provides a measurement that allows the comparison of different subjects regarding energy costs in physical activities [37].

In [38] two metrics are proposed for human activity (walking, stair climbing, chair-standing, and lying on a bed) based on high-density acceleration recordings from an accelerometer sensor placed on the waist. The start and end times of each activity were recorded by a lab technician for a more detailed description. These two metrics are based on two concepts: Time Active, which is a measurement of the length of time when activity can be distinguished from rest, Activity Index (AI) is a measurement of the relative amplitude of activity comparative to rest. In this study, they start by normalizing the data on a scale that can be interpreted in units of intensity of activity, then they measure using the same type of accelerometer, from different people and locations, in order to have comparable and similar interpretation data, finally, this approach automatically mimics human information processing. AI is a complement for the Time Active, which only emphasizes the time spent active without information about how active the subject is, like running and walking without stops for 15 minutes give the same Time Active but a different AI. AI is defined as the “total acceleration at a particular time point after removing the global average acceleration relative to rest” [38], thus any device can be used in an unbiased way.

In [39] the procedure used is composed of two phases, being the first one the calibration sample and the second one the validation sample. These phases are then reported to the laboratory between 21 hours (9:00 p.m.) and 24 hours (12:00 midnight), for an overnight polysomnographic (PSG) recording using standard sleep recording montage along with an actigraphic recording. The Actigraph was placed on the dominant wrist to record the sleep and the wake activities during the recording night. The data recorded with the Actigraph was analysed using an actigraph data analysis software (ADAS. This software allows the visual inspection of patterns of activity based on the actigraphic data, this data can be manipulated to yield statistical values for a number of actigraphically derived variables, such as sleep efficiency index (SEI), wake after sleep onset (WASO), sleep onset latency (SOL) and others. Furthermore, amplitude, periodicity, and phase of the circadian rhythm in activity patterns can be determined with the added smoothing and autocorrelation functions.

2.6. Accelerometry data reduction

There are five issues that are important to consider when processing accelerometer data: identifying the wearing period of the day (accelerometer), spurious data, compute outcome variables and aggregating days of data and extracting bouts of moderate to vigorous physical activity (MVPA). The clarification of these problems and the standardization of accelerometry data reduction would significantly improve the ability to compare results across studies [40]. The study [41] emphasizes three key data reduction criteria, the number of valid days, the daily wear time and non-wear time. Finally, the extraction of MVPA bout is used to understand whether the subjects met the current physical activity recommendation, in our case the students need to perform about 60 minutes of physical activities, however, it's unlikely that

children will be able to sustain a high level of activity for 30 or 60 minutes, instead they have short bouts [42].

Data reduction techniques are used in order to reduce the number of data records by removing invalid data or produce summary data and statistics at different aggregation levels for various applications [43], these can be deduplication, compression, thin provisioning, sampling, BIRCH summarization. The deduplication technique typically happens at the storage block level, the system analyses the storage to check if duplicate blocks (contiguous set of bits/ bytes that form an identifiable unit of data, this term is normally used in word processing, network communication and database management) exist and gets rid of any redundant blocks. In case an application tries to change one block, that block is copied prior to modification so that other files that are dependent of that block can continue to use the version that stayed unmodified, avoiding this way a corrupted file. The data compression technique is used to reduce the size of a file, by removing redundant information from files, to reduce the disk space that is typically required. This is accomplished by using algorithms or formulas created with the purpose of identifying and delete the redundant bits of data [44]. The thin provisioning technique is used to complement the other two techniques, by providing a dynamic form of storage allocation.

By eliminating the pre-allocation of unused capacity, more data can be stored on the storage platform, this method provides an effective, on-demand storage consumption model [45]. The Sampling technique allows us to draw statistical interpretations about the unknown population from sample data, but it's viewed as an expensive resource and it is supposed that capturing population data is impossible [46]. Sampling can be used in the context of data reduction for data mining [47], [48]. The BIRCH technique is a clustering method for handling very large datasets, it starts by generating more compact summary that retains as much distribution information as possible, by concentrating on densely occupied portions, and then clusters the data summary instead of the original big dataset [49].

Figure 3 reproduced from [50] represents a general framework for accelerometer-related studies.

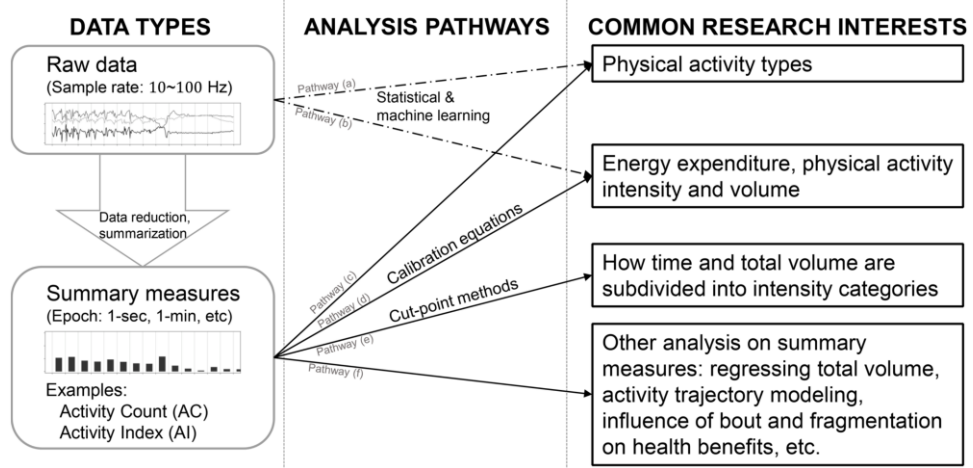


Figure 3 - The left panel represents the general data types, the right panel represents the 4 common research interests, the mid panel contains the 6 common analysis pathways between the data and the research interests [50].

In [38] the information captured from the accelerometer, is a high-volume and complex data that needs to be handled carefully and standardized to guarantee the validity and reproducibility of the metric.

Areas that were projected to be active show a wide range of variation both in terms of patterns and amplitude of the signal. The data was captured with a sample rate of $f = 10 \text{ Hz}$ for a total of 34 Subjects and each one was observed for four to five days. The subjects were only observed during in-lab sessions, not during in-home data collection. Once the presence or absence of activity is estimated, many types of metrics can be used to describe the rest of the data.

In [50], an ActiGraph GT3X+, which is a tri-axial accelerometer was used, in OPACH (Objective Physical Activity and Cardiovascular Health), to measure physical activity. It was configured to collect raw acceleration time series (x, y, z axes) at $f = 30 \text{ Hz}$. Then the ActiLife 6 companion software, could calculate axis-specific Activity Count (AC) ($AC_x^2 + AC_y^2 + AC_z^2$), and AC Vector Magnitude ($\sqrt{AC_x^2 + AC_y^2 + AC_z^2}$), which is the square root of the sum of the axis-specific AC), by using the raw acceleration time series. They also propose a metric called activity index (AI), which, according to the authors have several desirable properties, like transparency, ease of deployment, additivity and rotational invariance, this metric was then compared with the established AC. AI had the best results in distinguishing among various types of physical activities across different level of intensity, it also had the best overall performance predicting energy expenditure expressed in METs, and had the better predictive performance for classifying an epoch into various physical activities categories. One of the limitations of this study is the fact that only one kind of accelerometer was used, which is completely different from our case, in which all the devices were different, even though they were all smartphones. Another limitation given by the authors was the fact that the accelerometry data was collected only from hip-worn accelerometers, like what happens in our case, but with waist-worn accelerometers.

The work presented in [51], uses an Android application in order to collect accelerometry data from a tri-axial accelerometer. The smartphone was placed on the subject's waist, and the data was collected from 5 long-term activities: commuting, working at home, shopping and exercising.

The data collected from the accelerometer was smoothed with the moving average filter, $v_s(t) = \frac{1}{n} \sum_{i=t-n}^{t-1} v(i)$, using a window length of 15, where v is the original vector, v_s is the smoothest vector and n is the window length. The long-term activities are composed of simple activities, which are the ones they want to extract for a window length of w seconds. Each one of those simple activities are represented as a feature vector, and to calculate that vector they had the need to compute 14 features from each w seconds window. The statistical features computed over the window were: the mean value for each of the axis, the standard deviation for each axis, Pearson correlation for each pair of axes and the mean value of the derivatives for each axis. They also used two of the physical features described in [52] which are the average of the movement intensity $AI = \frac{1}{T} (\sum_{t=1}^T MI(t))$, and the variance of the movement intensity $VI = \frac{1}{T} (\sum_{t=1}^T (MI(t) - AI)^2)$, the movement intensity is computed as follows: $MI(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2}$, where $a_x(t)^2$, $a_y(t)^2$, $a_z(t)^2$ are the accelerations at time t from the w second window. At the end they conclude that the features proposed in article [52] can be used to recognize long-term activities. Furthermore, they extracted a set of features from the distribution of primitives and used a threshold in order to reduce the noise, which help them to increase the classification accuracy. At the end of this process, they have a set of simple activities that arose from each of the long-term activities. Then, they proceed to primitive generation to build blocks of long-term activities, to generate these primitives they perform clustering on all simple activities from the training set performed in the previous step. Once the clustering is finished each primitive match to the centroid of each cluster. Following histogram generation, which is responsible for representing the distribution of primitives for each long-term activity.

They also concluded that by using one tri-axial accelerometer, it was possible to accurately recognize the activities performed by the subjects.

In [53] it is mentioned that one of the first steps in the data reduction process is to screen the subject files for spurious data. Data found above or below the range of biological plausibility needs to be dealt with. The foundation for asserting the low level of plausibility is based on the notion that, if a subject is wearing an accelerometer, the accelerometer is capturing accelerometer values. The authors propose a set of data cleaning and data reduction rules of thumb to deal with incomplete activity monitoring data. They conclude that despite many limitations, accelerometers provide an accurate and feasible method of gathering detailed physical activity information in a free-living environment.

Our approach, reported in the following chapters, to reduce the complexity of analysing charts created from thousands of lines, (CSV files), save costs by using the accelerometers provided by the students smartphone, relies on the use of the REA metric [37], which is responsible for

the removal of the devices heterogeneity. This statistical metric reduces the complexity of charts being loaded, and analysed with lots of data, and hard to understand data, to a simple value, which is compared to a reference (HIRA). After those REA values are computed, the CSV file from which those values were calculated can be deleted, since the REA, for each activity will be added to the database. This will help reduce the amount of storage needed to store all the files uploaded from the smartphones, and it will also help reducing the complexity, summarizing data thanks to the metric REA. From the literature review, it is possible to argue that, subjects' activity comparison is not reliable using directly extracted features such as the magnitude or number of steps, since the devices used for the accelerometry collection are different, and students have very different physical traits.

2.7. Related work

Advances made in the semiconductor industry, which also boosted advances in mobile devices, have made it possible to build microprocessors smaller than a pinhead. This evolution enabled activity recognition systems to be used in our daily life, in forms of applications ranging from medical, engineering to leisure.

The application of these devices varies from both academic and consumer-driven. For instance, accelerometers in laptops protect hard drives from damage, in case the laptop were to drop while in use, the accelerometer would detect the free fall and would immediately turn off the hard drive [54]. They are also incorporated in a lot of personal electronic devices such as media players, gaming, smartphones. In smartphones, the accelerometer allows users to step counting, user interface control and switching between portrait and landscape modes [55]. This technology is also used in car safety, allowing the airbag deployment at the right time in case of crashing [55].

In medical applications, accelerometers can be used to monitor and diagnose patients [56], rehabilitation [57], child and elderly care [29], assistance for people with cognitive disorders [58]. In gaming applications, accelerometers can be used on gaming controllers (e.g. Wii Remote), control of a character [59], as a musical instrument [60].

In Jennifer Kwapisz et al.[61], different activities like walking, jogging, ascending stairs, descending stairs, sitting and standing, were recognized using machine learning using Android smartphones, to collect data. Twenty-nine users participated in this study. In this study, they achieved 90% of accuracy for walking, jogging, sitting, and standing, 61,5% while ascending upstairs and 55,5% descending downstairs.

In Edmond Mitchell et al.[62], different sports activities were recognized using machine learning, like walking, sprinting, tackling, dribbling the ball, from a collected database composed of soccer and field hockey activities. Fifteen users were recorded in five matches of soccer, while seventeen users were recorded for the field hockey. The maximum accuracy was 87% using a fusion of classifiers.

In Muhammad Shoaib et al.[63], by using accelerometer, magnetometer and gyroscope alone as well as combined, there are some situations where each performs better and which factors affect their performance. Six activities were recognized like waking downstairs, running, sitting, standing, walking upstairs and walking using an Android application. Overall, an accelerometer performs better than a gyroscope, however, when both are combined the results tend to improve.

2.8. Remarks

Physical education assessment like in any other subject has three types of pillars that are used to assess student's achievement/progression in physical education: diagnostic assessment, formative assessment, and summative assessment. The use of factors such as attitude, attendance and effort combined with subjecting rating of the student's motor performance, forms the way the actual model uses today in physical education evaluation. In order to complement the student's evaluation performance over the physical education classes, the accelerometer sensor will be used.

Accelerometers allowed the development of multiple innovative applications in many different areas. Judging by the wide research done in many areas, like medicine, sports, navigation, engineering, gaming. This sensor, improved people's quality of life, and quality of service. The analysed literature provided valuable insights relating to accelerometers, examples of some devices with an integrated accelerometer, sensor placement locations on the human body, and studies that used sensors to track motion.

An approximation with data reduction is made, more precisely accelerometer data reduction was a key element during the development of the proposed solution, and some techniques are presented with a brief explanation.

We identified two assessment metrics of effort [37, 64], as putative ways to circumvent the heterogeneity of the devices, and the differences in the students' physical characteristics, such as weight, height and age.

The assessment metric of effort REA allows the comparison between students without having to worry about their physical differences, this allows the teacher to complement his student's evaluation over the physical education classes, by tracking their performance.

3. Integrated assessment environment architecture

3.1. Introduction

In this chapter is discussed how the accelerometry data is handled. First is given a brief explanation about the mobile application that was used to capture the accelerometry data. Following an explanation of the data model, the software that the server needs to run, the registry system that was created for the webpage to give students access to their own data. Finally, is shown how the webpage displays the data for both the students and the teachers.

3.2. Mobile Client

A mobile client [37] is essential for collecting the accelerometry data, for that, the students need an Android version superior to 2.2. After the mobile client is installed in the student's smartphone, they need to execute the application, and insert the user information which is displayed in the app drawer (see Figure 4).

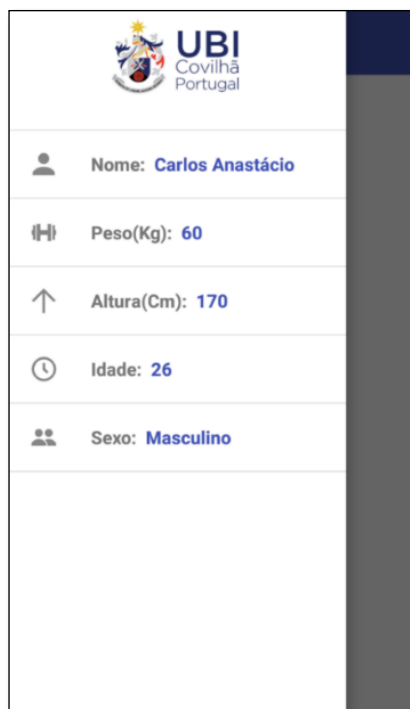


Figure 4 - Mobile Client with the drawer activated.

After those steps are complete, the students need to calibrate the sensors due to accelerometer reporting slightly wrong values, to do so, they need to place their smartphones on a flat surface, click on “Calibrar” and wait a few seconds. When the user information has been added and the smartphone calibrated, the user is ready to start capturing accelerometry values (see Figure 5).

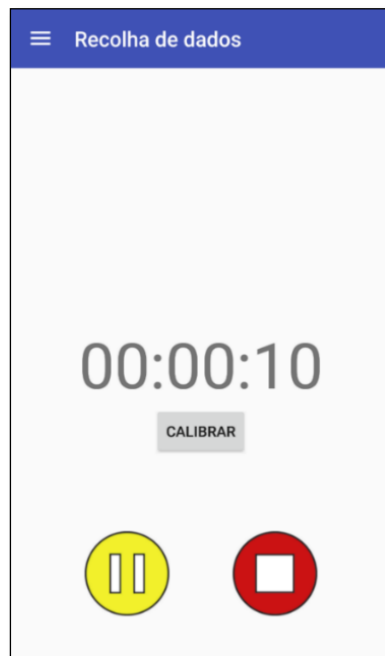


Figure 5 - Mobile Client capturing accelerometry data collection.

If a wireless connection is available after the students stop the capture, the values as well as the information provided by the students (Figure 4) will be uploaded to the server, if there is no connection available, the values are stored on the smartphone and then uploaded when a connection is available. After the values are uploaded to the server, the file will be deleted from the students' smartphone. For users to collect data with their smartphones, they need to have at least 75 Megabytes of free memory space available. The application uses an android service [65], when is recording accelerometry data, allowing the accelerometry collection to run in the background indefinitely, this way users can interact with their smartphones without affecting the accelerometry data collection. While data is being collected, a notification is displayed with the current sensor values readings, from the three axis (x,y,z) (see Figure 6).

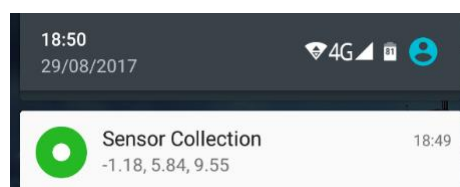


Figure 6 - Notification during accelerometry collection.

3.3. Data model

The database model (See Figure 7) was inspired on the one developed by a former student [37], there was a need to expand the data model to be able to handle some functionalities that were needed for this solution. Some of the functionalities are, the creation of a login system that would allow scholars the tracking of their own performance over time, and at the same giving the teacher a way to track their students' performance, helping to evaluate their performance over the physical education classes, and at the same time giving the teacher functionalities on his homepage.

The entity professor is responsible for storing information related to each professor registered on the system. Since one professor can teach one class, only one class can be taught by a teacher, this way generating a table called professor_class, which is responsible for storing the professorID, and the classID.

The entity activities_rea, was needed to keep track of the beginning and ending of each activity, this information is sent to the database to simplify the teacher's task. The teacher only needs to insert the beginning and ending of each activity in his home page, and a runnable JAR is responsible for calculating the running equivalent activity (REA), and storing those values in the database on the table user_rea. This information can then be displayed in the teacher view.

The entity username works like a username pool, each student and professor must have one in order to login, and this way, we can keep their username unique, the admin must manually set the field professor to let him access his homepage, to keep students from registering as professors.

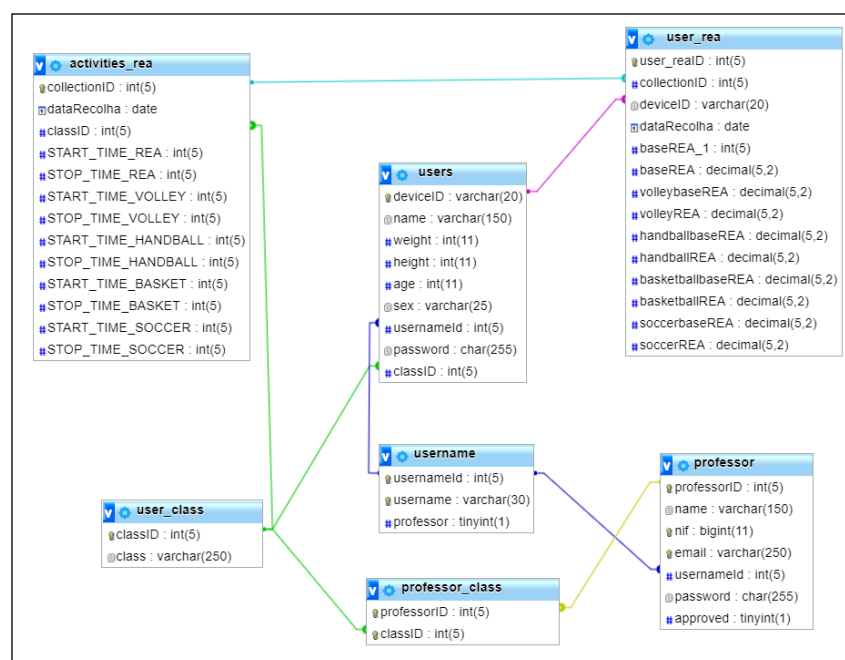


Figure 7 - New Database relational model.

3.4. Server Application

The server is located at Universidade da Beira Interior, Covilhã, running Linux Ubuntu 14.04 64 bits. The server runs MySQL version 14.14 which is necessary in order to work with the database. It also runs PHP version 7, which is mandatory to run a PHP script [37] that uploads the accelerometry data completely autonomous, creating the required folder structure (Table 2), inserting the user information in the database and moving the received files to their respective locations, and it's also used on the front-end application.

Table 2 - Server Folder Structure

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

On the server, each student will have their respective folder, identified by the device id generated on the mobile client, where all the CSV files are stored, in case a student uploads more than one CSV file per day, a number is added at the end of the filename (Table 2). The server also runs apache2 which allows students or teachers to check their own data, via browser, or the data from all the students (in case the user is a teacher). The server is also responsible for analysis tools, that extract information and generate REA charts.

3.4.1 Registry and Login Systems

The registry process starts in the mobile client, where the students fill the formulary, the application is responsible for inserting the data filled by the users in the database. After that first registry, and after the student's formulary information is uploaded to the server, they can proceed to the registry in the web application, to do so, they need to complete the registry formulary with all the necessary data for their registration to be successful. For a professor to register on the system, he needs to insert a username, email, password, name, and tax number? (NIF), since the process needs to be controlled, to avoid student's registration as professors, a field approved was added to the table professor, once a teacher registration is complete, that field is set as 0. To proceed to the login that value needs to be changed to 1 by the administrator. After the registration is complete, and the field approved is set to 1 by the administrator, the professor can log in. The fields username and password have a minimum size of 4 characters and 6 characters respectively, and the field username is a unique field. When the registration process has been completed with success, the user can proceed to the login. In order to login the students only need their username and password. After that process is complete, students and teachers can visualize their own information, and in case of a professor, visualize his student's performance. The database has an entity called username, which works as a pool of usernames, since students and teachers are two different entities, maintaining this

way their uniqueness, as can be seen in the Figure 8, the field professor is used to hide sensitive information about the collections from the students.

The password fields are being encrypted with password_hash, using the PASSWORD_DEFAULT [66], which uses the bcrypt algorithm. When the users are logging in, the password is verified using password_verify [67], which verifies that the given hash matches the given password, it returns true if the password and the hash match, or false if they don't match.

3.4.2 Teacher view

This view allows the teacher to perform a series of tasks, like submitting the times of each activity to calculate the REA (see Figure 8), displaying the results calculated in a table. After these times are submitted, they will be inserted on the table activity_rea of the database. These times will be needed to calculate the REA of each activity during a determined time. After the REA values are calculated they will be inserted on the table user_rea of the database.

Turma	Nome	Data	BaseREA	BaseREA1	VolleyREA	Volley	handballREA	handball	basketballREA	basketball	soccerREA	soccer
IPA	Jose carlos	2017-05-08	68.53	1	0.26	26.04	0.54	52.84	0.62	61.03	0.54	52.91
IPA	Neuza	2017-05-08	77.09	1	0.23	18.05	0.57	44.23	0.62	47.78	0.45	34.94
IPA	Sofia	2017-05-08	89.32	1	0.27	23.74	0.17	15.37	0.22	19.75	0.16	15.67
IPA	Carolina	2017-05-08	25.62	1	0.72	18.49	0.83	21.33	0.76	18.06	0.58	14.91
IPA	Vanessa	2017-05-08	57.63	1	0.40	15.09	0.61	23.10	0.83	31.41	0.58	21.86
IPA	Gonçalo Simão	2017-05-08	18.01	1	0.78	14.11	0.99	17.80	0.93	16.66	0.92	16.48

Figure 8 - On the left side are inserted the beginning and the ending of each activity. On the right side are displayed the last calculated values.

The calculated REA values can be displayed by class, date or all the results calculated at the time. All the information about the collection times can also be displayed by class, date or all the collections done to date (see Figure 9).

Turma	Nr.º Coleção	Data	Tempo Inicial Rea	Tempo Final Rea	Tempo Inicial Voleibol	Tempo Final Voleibol	Tempo Inicial Andebol	Tempo Final Andebol	Tempo Inicial Basquetebol	Tempo Final Basquetebol	Tempo Inicial Futebol	Tempo Final Futebol
9ªA	1	23-05-2016	6	8	11	24	27	41	44	56	60	73
9ªA	2	30-05-2016	10	12	24	37	39	53	55	67	68	75
9ªA	3	02-06-2016	6	8	10	23	25	38	39	52	57	75
9ªB	4	16-11-2016	0	2	10	17	19	37	40	52	55	68
9ªB	5	03-05-2017	0	2	11	24	27	39	41	54	58	66
9ªA	6	08-05-2017	1	3	6	19	22	34	38	50	54	66

Figure 9 - Accelerometry collections information.

It also has a control panel, that allows the teacher to check the classes he teaches, add, and remove students from a class, displaying on a table all the students that are “registered” in a class already, he can also check the registered students by class.

The home page displays all students who are enrolled in a class taught by the teacher logged in. The teacher only needs to select the student from the list displayed on the left (see Figure 14), to retrieve the charts and all the information related to the selected student, this displayed information is the same as the one displayed in the student view.

The charts (see Figure 10) were generated for each student with the REA values that were stored in the database as well as the data of each accelerometry collection. In order to generate the charts, Google bar charts [68] was used.

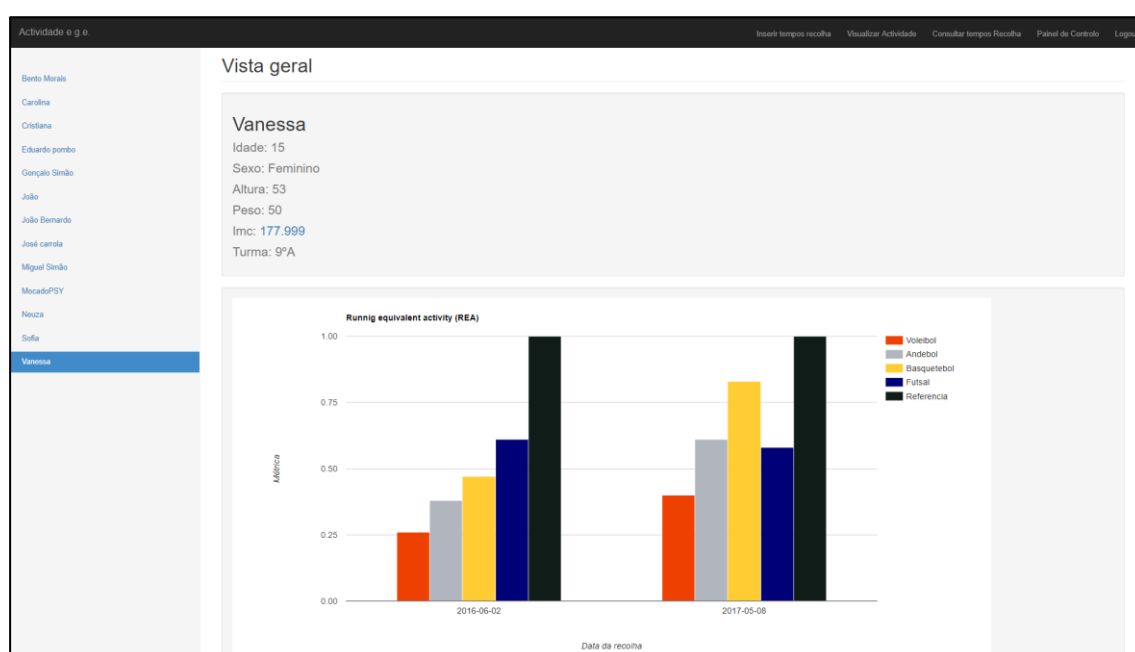


Figure 10 - Teacher's Home page.

3.4.3 Student view

This view is responsible for displaying all the information related to the logged student, such as weight, height, BMI, class as well as the generated charts obtained from their accelerometry collections data, with this data being collected throughout physical education classes. First, students need to complete their registration process, and after the login process is complete they will be redirected to their homepage (see Figure 11).



Figure 11 - Student's page.

3.5. Remarks

Adapting technology to physical education classes, tends to attract the student's interest, the accelerometry data collection, can be seen as a way to make students more competitive among themselves, and a way to help the teacher as a complement to the evaluation over the curricular year.

The mobile client wasn't changed due to the fact, that some of the students that were collecting accelerometry data this year, also collected data last year, and some of them still had the application installed on their smartphones from the previous year. In a future implementation, the mobile client should also have a unique field, for the students to insert, like a username or email.

Unfortunately, not all the students from each class were able to collect accelerometry data during any of the collections, due to other operating systems on their smartphones, parent's permission or simply didn't want to do the collections. The data model can be changed to, support collections from other schools.

The charts displayed on the teacher and student views, are only shown after the teacher submit the times of each activity performed during a collection, because to calculate the REA for all the activities the teacher needs to input the beginning and ending of each activity.

4. Analysis of collected data

4.1. Introduction

In this chapter, the experiments that were made using the accelerometry data that was collected in the physical education classes are discussed. First is given an explanation about the collection procedure, and then are presented the students characteristics.

These experiments comprised for the following physical activities: volleyball, handball, basketball, and futsal. This chapter displays REA values on each activity using three different approaches, by displaying charts with the data obtained during the collections. Each approach displays two charts for each activity, the first one being responsible for displaying the REA values captured during two collections, and the second ones demonstrates the students that were able to do three collections during the curricular year. Students 12 - 13 only managed to perform one collection, so since it won't be possible to evaluate their progress, they won't appear on the next subtopics.

Figure 12, presents schematically the complexity reduction via REA, that is the base of this study, first the setup shows how the accelerometry data is captured, and has a picture of one of the collections with students performing basketball, the high intensity running (HIRA) and basketball charts were generated from the accelerometry data that is on the csv files, with the time (millisecond) being displayed on the X axis, and the magnitude being displayed on the Y axis, and finally, the REA values for the two students during the basketball activity. As can be seen the complexity of the two basketball charts, was reduced to two chart columns with the REA for each student.

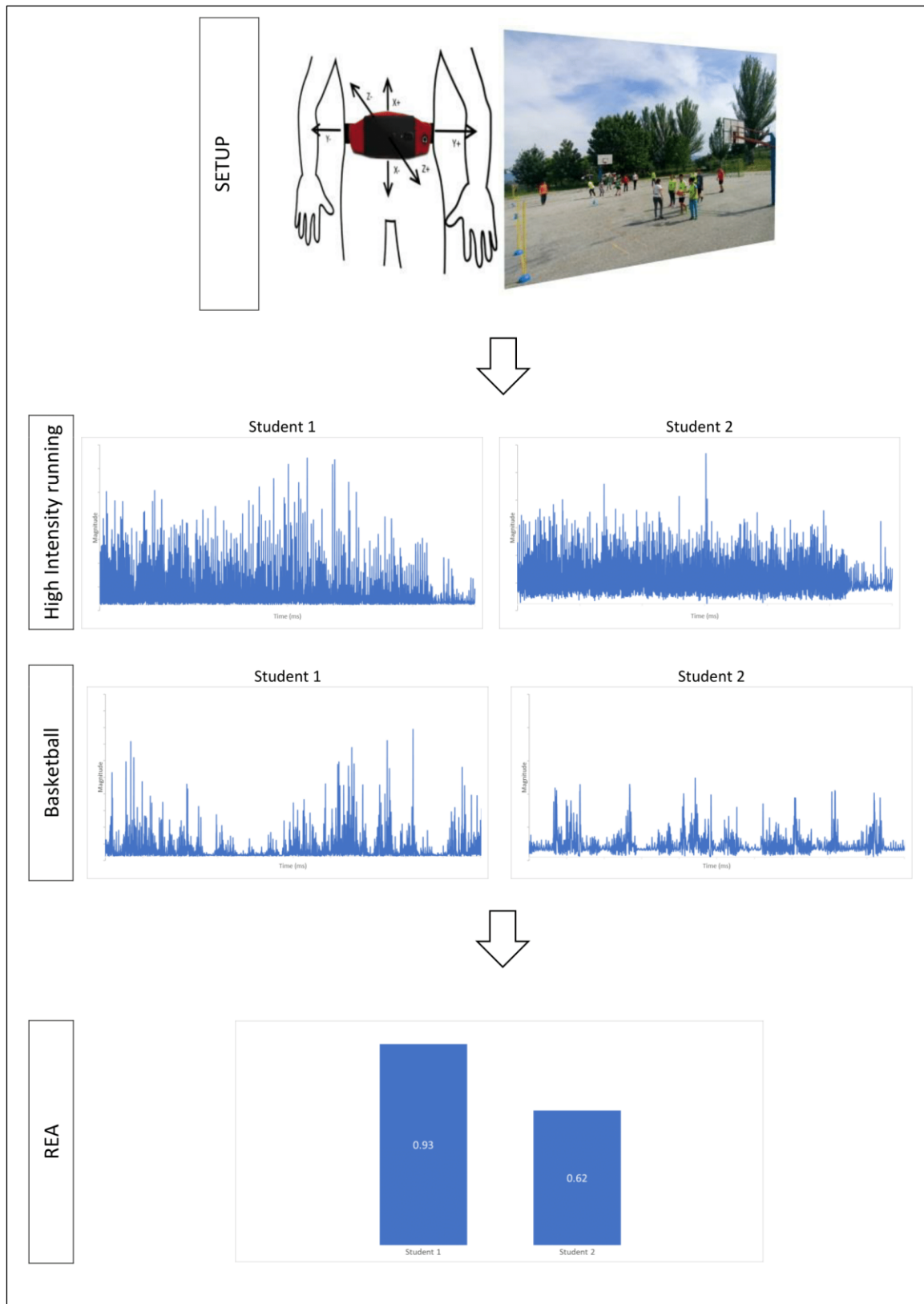


Figure 12 - Complexity reduction via REA.

4.2. Collection procedure

Four data collections were scheduled, allowing us to visualize the student's progression. Professor F. Ferreira conducted the class, instructing the students through the different activities. The activities are composed of 4 different sports: volleyball, handball, basketball, and futsal, and they were performed with team matches of equal team size and equal match length.

To collect the accelerometry data, a smartphone bag was provided to the students, that bag needs to be placed on their waist, to allow them the execution of the activities in the most comfortable way, and without disturbing their performance of the physical activities. The students need to position their smartphone, on their smartphone bag, and the phone needs to be placed with the back facing forward, it's top pointing left, and must be in front of the subject waist (see Figure 13).

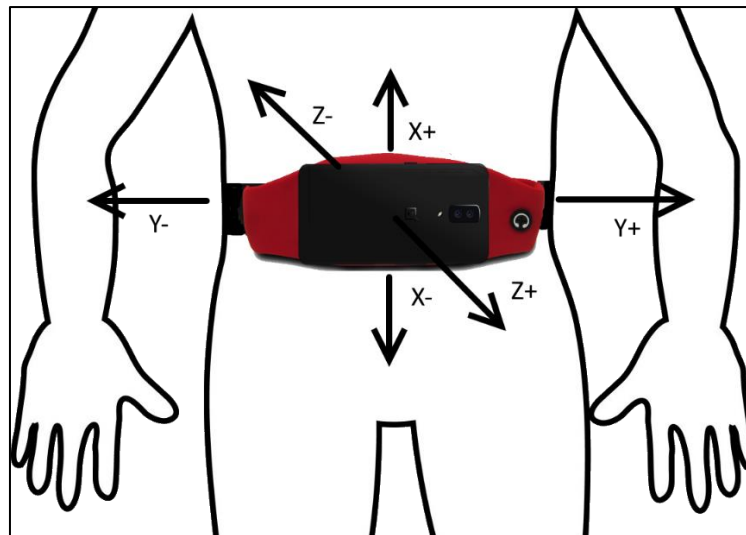


Figure 13 - Smartphone position during accelerometry collection.

Every student needs to start the data collection at the same time, allowing this way an easier and more accurate activity identification and extraction, and making the process easier for the teacher. The entire class was recorded without any interruptions, allowing the identification of each activity by a timestamp. Each activity had an estimated time (see Table 3), between them there were 2 minutes breaks, to allow the students to rest, drink water, and prepare for the next activity. Due to some delays, like students spending more time than the break time, or the teacher giving instructions for the next activity, pauses tend to take longer, which led to timing the beginning and ending of each activity with a chronometer, granting this way more precise times, which will influence the REA calculation for each activity, therefore making these values more accurate (for each activity as well as overall).

Table 3 - Physical activity list.

Activity	Duration	Description
Volleyball	13	Team match of 3x3
Handball	13	Team match of 3x3
Basketball	13	Team match of 3x3
Futsal	13	Team match of 3x3

From all the collections made, datasets were successfully received from 13 students, only six used the same smartphone during all the collections, other six changed at least once, and one changed twice. (see Table 4).

Table 4 - Number of collections, devices and description made by each student.

Students ID	Number of Collections	Number of Device used	Description
Student1	2	1	-
Student2	2	1	-
Student3	2	2	Each collection using different devices
Student4	3	2	First two collections with one device, third with another one
Student5	2	1	-
Student6	2	1	-
Student7	3	2	First two collections with one device, third with another one
Student8	2	2	Each collection using different devices
Student9	3	3	First two collections with one device, third with another one
Student10	3	2	First two collections with one device, third with another one
Student11	3	2	First two collections with one device, third with another one
Student12	1	1	-
Student13	1	1	-

4.3 Students physical characteristics

This study was made from students attending the 9th of the Portuguese education system, 6 students from classes A, and 7 students from class B. In total 13 students, 8 men and 5 women participated in this study. In table 5 are available the average and range of each physical trait.

Table 5 - Students physical characteristics.

Features	Men = 8		Women = 5	
	Average	Range	Average	Range
Body mass (kg)	60.0	45-72	53.4	46 - 60
Height (cm)	171.9	160-189	158.4	152 - 166
Age (Years)	14.9	14-18	14.6	14 - 15

4.4. Illustrative example

After the collections, the data will be uploaded (if there is an internet connection available) from the student's smartphones to the server, to be analysed. The first that needs to be done is the calculation of the average magnitude of all the three-axis using the formula (3), between the timestamp of each activity, in order to separate them. Then, to calculate the REA for each activity, the formula (2) must be used, where the $avgMagn(Activity)$, is divided by the $avgMagn(RunHigh)$. Different REA values were obtained for each activity performed, and the results obtained with each approach differs from each other.

The activity values were calculated using three different approaches to compare results. The first one consists of calculating the REA for all activities by only using the first captured HIRA as the calibration activity for all the collections, the second one using the HIRA calculated on each collection, and the third one by calculating the average of all the HIRA values that were captured, and subsequently calculating the REA values for all the activities performed by the students.

From Figure 15-38, in the caption with the list of students, note that the ones with an asterisk near them, have changed their smartphone at least once, and the number of devices utilized by each student during all the collections performed can be checked on the Table 4. The values of the HIRA will be equalled to the reference, which is 1, and then the REA values calculated will be compared to that reference.

4.4.1. Calculate REA using the first HIRA

In the first approach, the first captured HIRA value is used to calculate the REA's for all the collections, (see the HIRA values on Table 6) removing the need to repeat the HIRA on the following sessions. This approach can also be applied to any new activity that might need to be

evaluated. From 13 students, 6 changed their smartphone at least once, which will lead to biased REA values, due to the different sensibility of the accelerometers, which also lead to discrepant REA values based on that HIRA calculation, since, the first captured HIRA value would be used to compare all the activities performed onward by the students during their physical education classes. Figures 15, 17, 19 and 21, display the REA values for the first two collections, while Figures 16, 18, 20 and 22 displays the students that were able to do three collections.

Figure 14 displays a chart with the magnitude values in the volleyball timestamp, for the student 1, as can be seen in Figure 15, the REA values for each collection are 0,26 and 0.21 respectively.

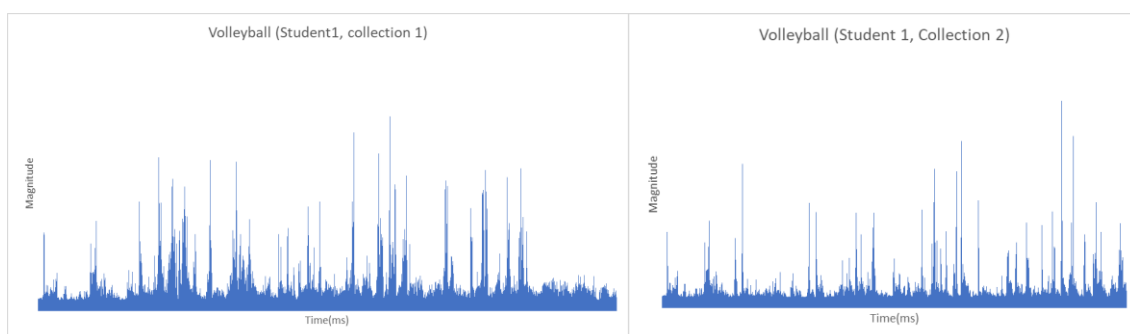


Figure 14 - Volleyball magnitude values from collections 1 and 2 for Student 1.

In Figure 15, the students 2 and 10 performed near the reference value 1, which compared to the other students is above the average (see Table 7). The overall REA values tend to be lower than the ones from the other activities, since volleyball is a positional sport, where students don't have the need to run as much as in the other activities. As can be seen in Table 7, volleyball is where students incline to have the smallest REA values, and where the standard deviation is more closely distributed.

Figure 16 displays the chart for students that performed three collections, student 10 outperform his colleagues.

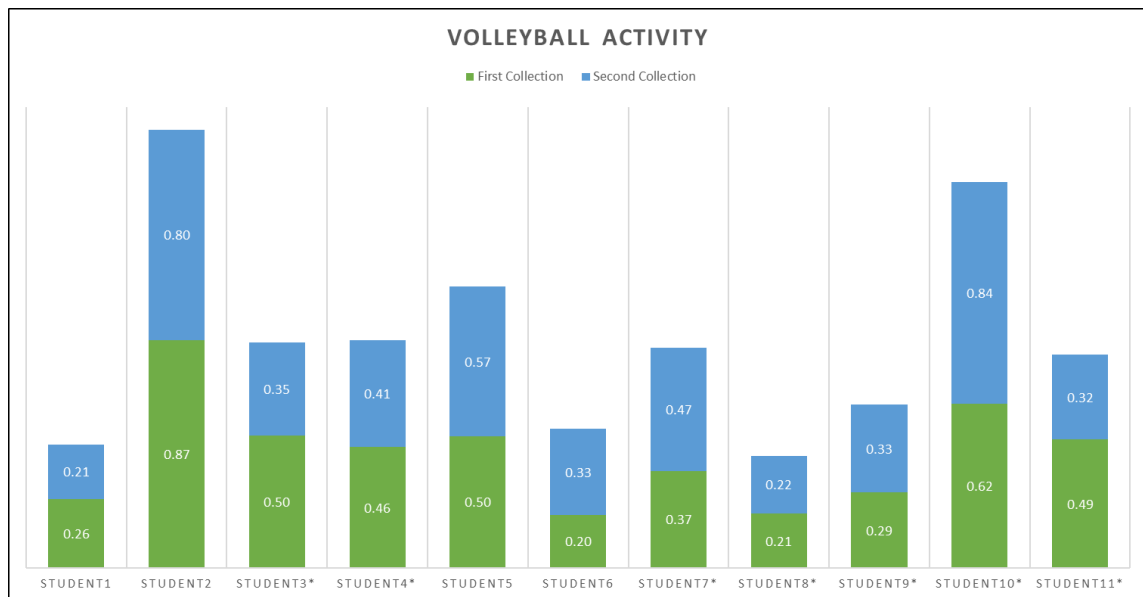


Figure 15 - Volleyball REA for the first two collections calculated using the first HIRA value captured.

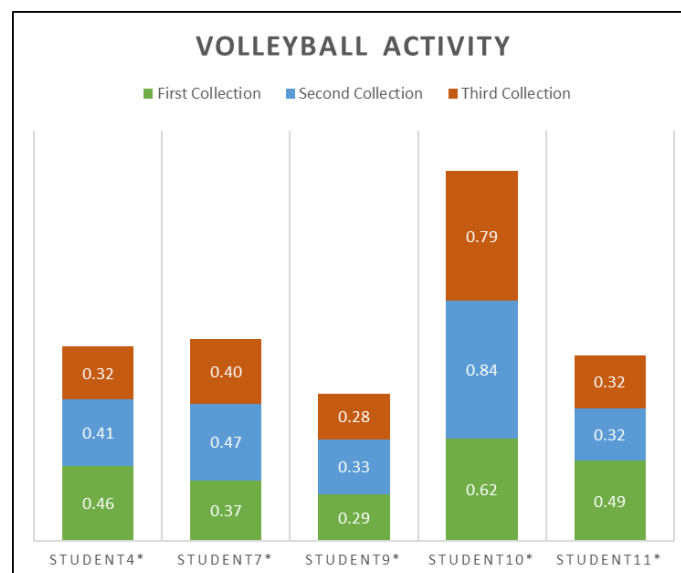


Figure 16 - Volleyball REA for students with three collections calculated using the first HIRA value.

In Figure 17, students 2 and 10 performed above the reference level, both on their second collection, and student 3 and 5 performed high REA values. Since handball has more movement than volleyball, the overall values tend to increase over the volleyball REA values. As can be seen on Table 7, this is the second activity with the lowest REA values, and is the second activity with the highest standard deviation.

Figure 18 displays the chart for students that performed three collections, student 4 had a high REA value, while student 10 outperformed the reference level.

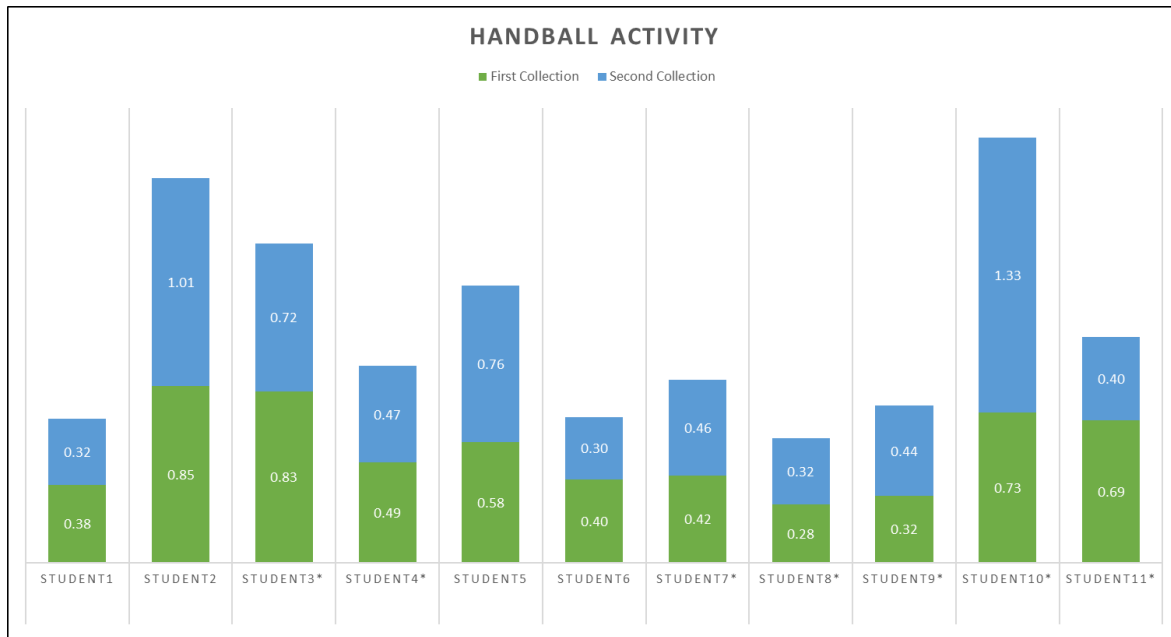


Figure 17 - Handball REA for the first two collections calculated using the first HIRA value captured.

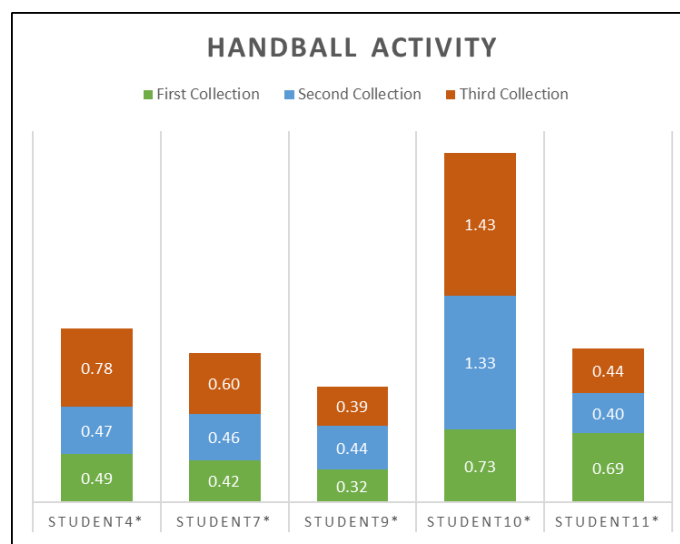


Figure 18 - Handball REA for students with three collections calculated using the first HIRA value.

Figure 19 displays the REA values for basketball, which is the second activity with the highest REA, and is the second activity with the lower standard deviation (Table 7). Four students performed near the reference level, while student 2 and 10 outperformed the reference value.

Figure 20 displays the chart for students that performed three collections, with student 4 having a high REA value and student 10 outperforming the reference level also on the third collection.

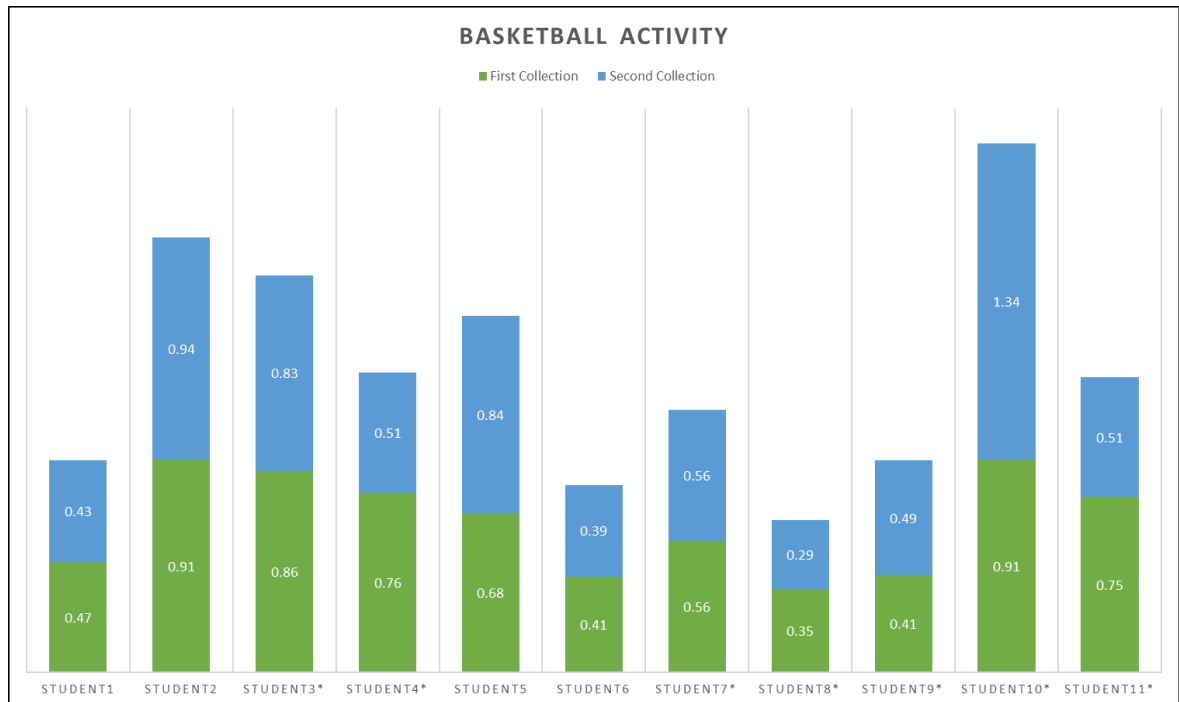


Figure 19 - Basketball REA for the first two collections calculated using the first HIRA value captured.

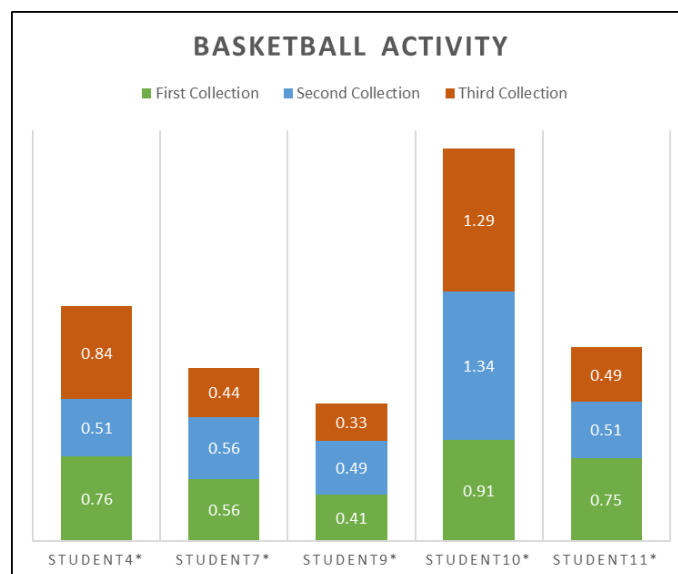


Figure 20 - Basketball REA for students with three collections calculated using the first HIRA value.

In Figure 21, are displayed the REA values for futsal, the activity with the highest REA values, and also the highest standard deviation (see Table 7). On this activity, almost all students had a good performance, with two students having outperformed the reference level, and another one equalled the reference. Figure 22 displays the chart for students that performed three collections, student 7 almost reached the reference and student 10 outperformed it.

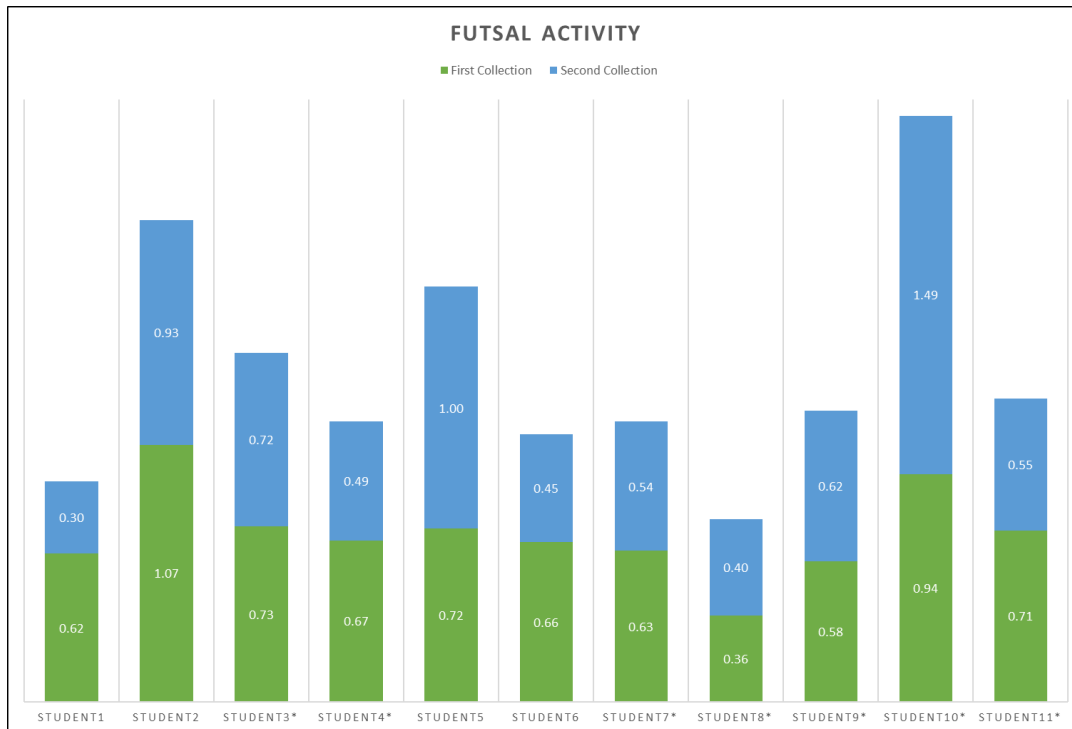


Figure 21 - Futsal REA for the first two collections calculated using the first HIRA value captured.

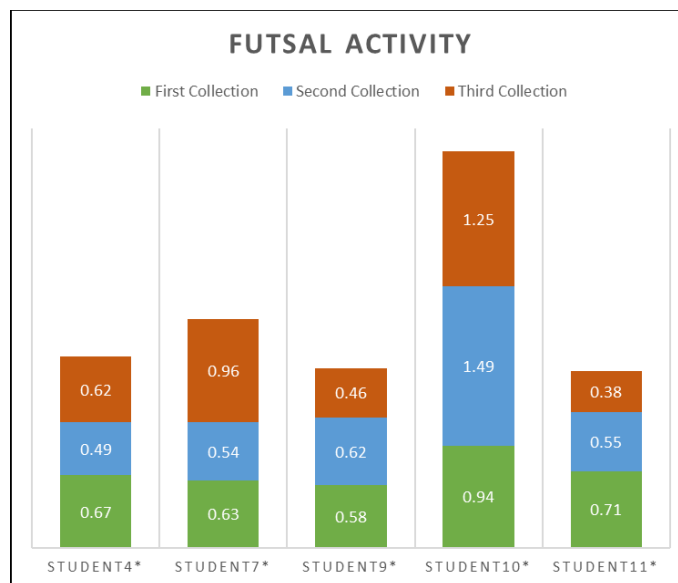


Figure 22 - Futsal REA for students with three collections calculated using the first HIRA value.

This approach removes the need to perform the HIRA during all the collections performed by the students, and it is good to understand the student's progression, due to the HIRA value used during all the collections being the first one captured. One disadvantage is the effectiveness of this approach, since the students changed their smartphone during the collections, which will have an affect in the calculated REA, because accelerometers have different sensibilities. In case there is no device change, this approach would remove the need to perform the HIRA during the beginning of each collection, the students would need to perform this activity during

the first collection and the calibration value would be used to calculate the subsequent collections REA values.

Table 6 - Students calibration activity (first collection values).

Base Values	
Student1	72.71
Student2	17.67
Student3	73.45
Student4	56.73
Student7	80.36
Student8	132.12
Student9	71.87
Student10	32.5
Student11	99.72

The values from the charts (Figures 15-22) can be compared to the activity average, which are represented in Table 7.

Table 7 - Calibration activity average, standard deviation, and REA values average using the first base value calculated.

	Reference	Volleyball	Handball	Basketball	Futsal
Average	1	0.45 ± 0.21	0.60 ± 0.29	0.66 ± 0.27	0.72 ± 0.30

4.4.2. Calculate REA using each collection HIRA

The second approach relies on the HIRA values that were captured during each accelerometry session used as the calibration activity (see Table 8), when compared to the first method, allows the change of device being used, because it's mandatory to execute the HIRA during all the collections. From Figure 23-30, are displayed the REA values for each activity, calculated using each HIRA obtained on the collections (Table 8).

In Figure 23, no student was able to overcome the reference value on the volleyball activity, but student 2 and 10, performed near the reference. As can be seen in Table 9, volleyball continues to be the activity with the lowest REA values, and also the activity with the lowest standard deviation. Figure 24 displays the chart for students that performed three collections, on the third collection no student was able to overcome the reference value.

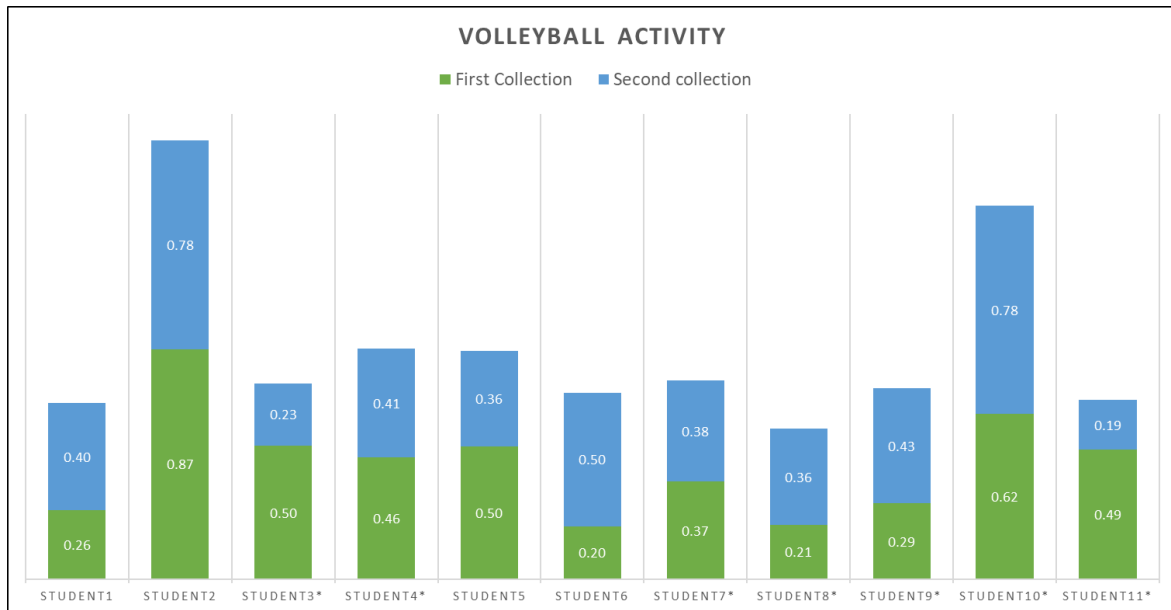


Figure 23 - Volleyball REA for the first two collections calculated using each collection HIRA value.

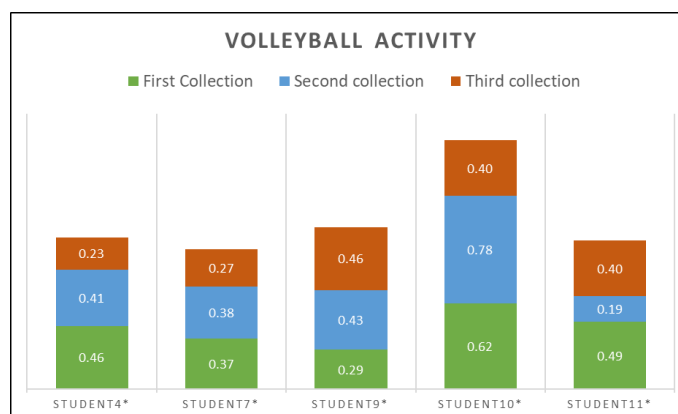


Figure 24 - Volleyball REA for students with three collections calculated using each collection HIRA value.

In Figure 25, student 10 was able to overcome the reference on his second collection, while student 2 was near the reference also in his second collection, handball continues to be the third activity with the highest REA and is the second activity with the lowest standard deviation, as see in Table 9. Figure 26 displays the chart for students that performed three collections, on the third collection no student was able to overcome the reference value.

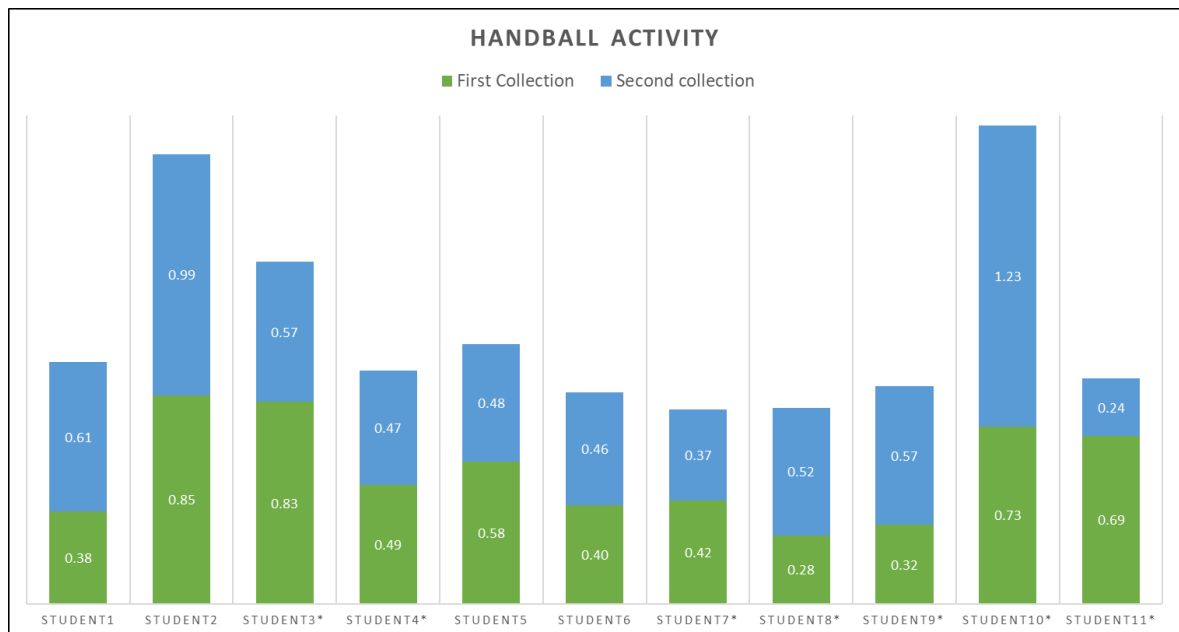


Figure 25 - Handball REA for the first two collections calculated using each collection HIRA value.

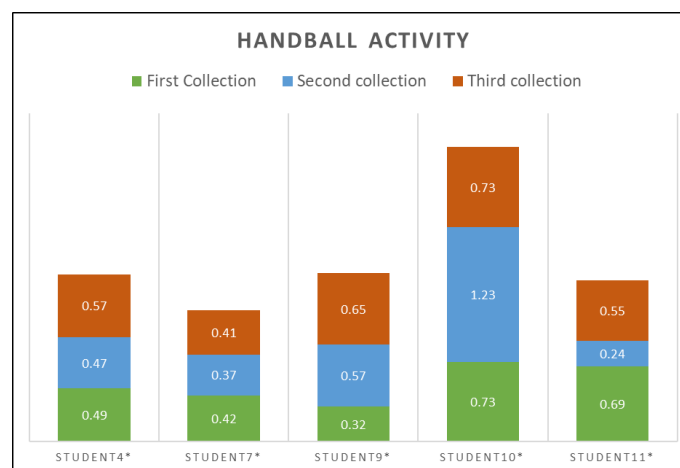


Figure 26 - Handball REA for students with three collections calculated using each collection HIRA value.

In Figure 27, student 10 was able to overcome the reference also on his second collection and had a high REA value on his first collection, with student 2 near the reference in his both collections. Basketball is the second activity with the highest REA values and has the same standard deviation as handball and futsal, as can be seen in Table 9. Figure 28 displays the chart for students that performed three collections, on the third collection no student was able to overcome the reference value.

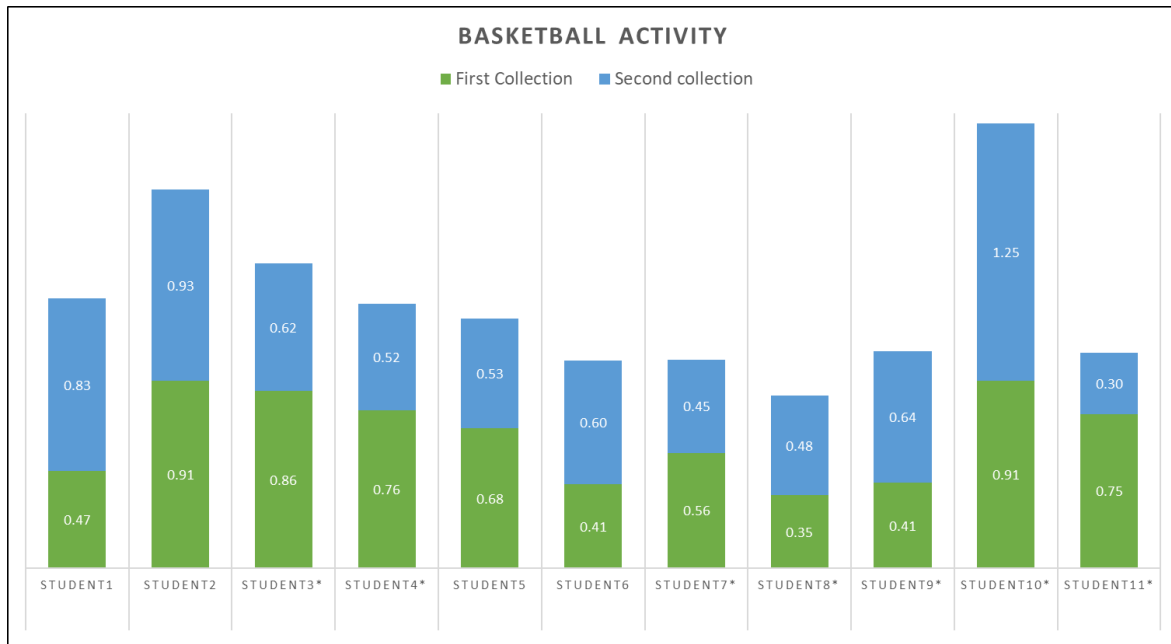


Figure 27 - Basketball REA for the first two collections calculated using each collection HIRA value.

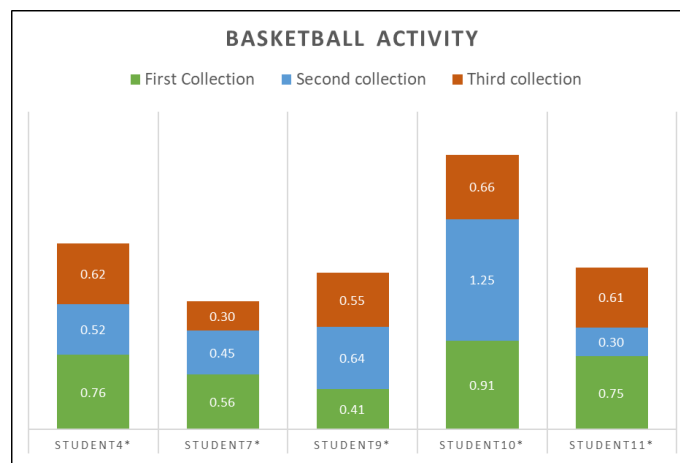


Figure 28 - Basketball REA for students with three collections calculated using each collection HIRA value.

Figure 29 displays the REA values for futsal, which is the activity with the highest REA values, and has the same standard deviation as handball and basketball (Table 9), in this activity, students 2 and 10 overcame the reference in their first collection and third respectively, and students 3, 9 and 11 had high REA values. Figure 30 displays the chart for students that performed three collections, on the third collection no student was able to overcome the reference value, but student 9 had a high value.

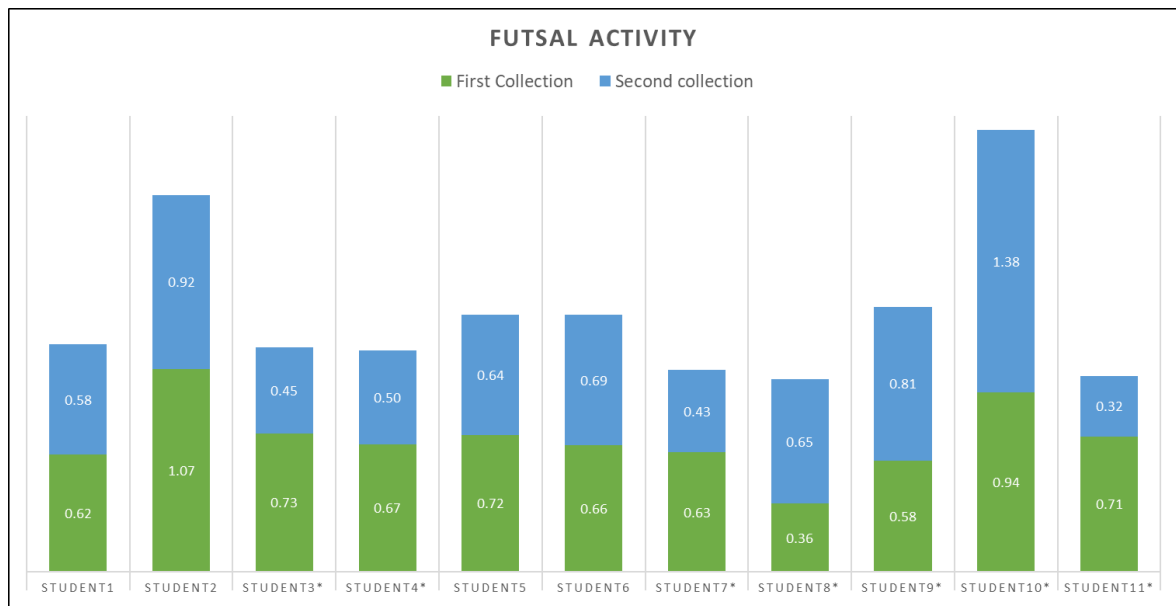


Figure 29 - Futsal REA for the first two collections calculated using each collection HIRA value.

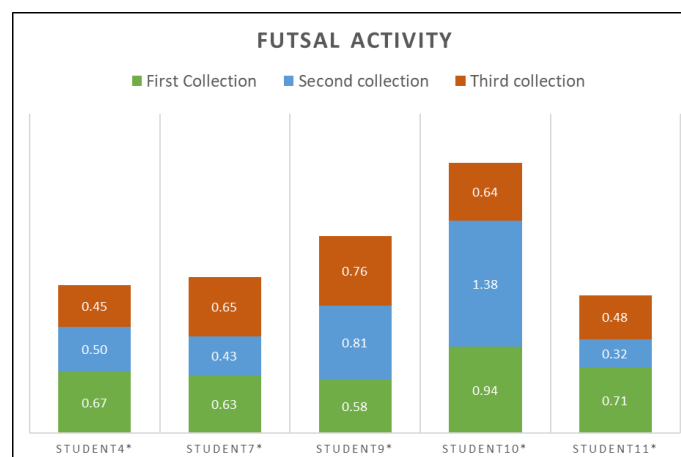


Figure 30 - Futsal REA for students with three collections calculated using each collection HIRA value.

This methodology is effective because it allows the teacher to track the student's progress during each collection individually, which doesn't happen with the previous methodology, since all the collections would be based on the first HIRA REA value. It also allows the teacher to evaluate the student's overall performance after all the collections have been made. One disadvantage of this methodology is that the students need to perform the HIRA during all the collections, which doesn't happen in the first methodology, where students only need to perform the HIRA once. This approach has the advantage of students might changing their smartphones, cause there performance is always derived from the new device.

Table 8 - Students calibration activity during all collections.

	Base Values First Collection	Base Values Second Collection	Base Values Third Collection
Student1	72.71	37.63	-
Student2	17.67	18.01	-
Student3	73.45	98.53	-
Student4	56.73	56.41	77.09
Student7	80.36	99.34	119.27
Student8	132.12	80.75	-
Student9	71.87	55.27	43.55
Student10	32.5	35.05	63.59
Student11	99.72	171.45	79.53
Student12	45.62	72.09	-
Student13	114.23	74.54	-

The values from the charts (Figures 23-30) can be compared to the activity average, which are represented in Table 9.

Table 9 - Activities average and standard deviation, using each collection base value.

	Reference	Volleyball	Handball	Basketball	Futsal
Average	1	0.42 ± 0.17	0.57 ± 0.22	0.63 ± 0.22	0.67 ± 0.22

4.4.3. Calculate REA using the average of all the HIRA

The third approach relies on calculating the average of the HIRA values captured during all the accelerometry collections and using that average as the calibration, for each subject (see Table 10). From Figure 31-38 are represented the REA values for all the activities performed, using the mean of all the base values, which can be compared to the student's average (see Table 11). This method removes the disparity in student's base value, and subsequently the activities REA values become more constant, since the same value is used to calculate the REA for all the activities, one drawback is that it doesn't permit the teacher to check his student's performance on each collection separately, since the base value is based on multiple collections. When comparing the activities REA average from all the three methods, (see Tables 7, 9, 11), this one has the lowest values, because the discrepancy revealed in the other two methods was reduced, because the HIRA used to calculate the REA is the average of the collections, each time a new collection is inserted for a student, all his REA values will change.

Table 10 - Students average calibration activity from all collections.

Average Base Values	
Student1	55.17
Student2	17.84
Student3	85.99
Student4	63.41
Student5	58.86
Student6	94.39
Student7	99.66
Student8	106.44
Student9	72.61
Student10	56.23
Student11	116.90

Figure 31 represents the REA for the volleyball, in which no student was able to overcome the reference value in any collection. Student 2 was near the reference on both collections. In this case student 10 kept increasing his effort during the calibration activity on his first two collections. As can be seen in Table 11, volleyball continues to be the activity with the lowest REA values, and with the lowest standard deviation. Figure 32 displays the chart for students that performed three collections, no student was also able to overcome the reference value on this collection.

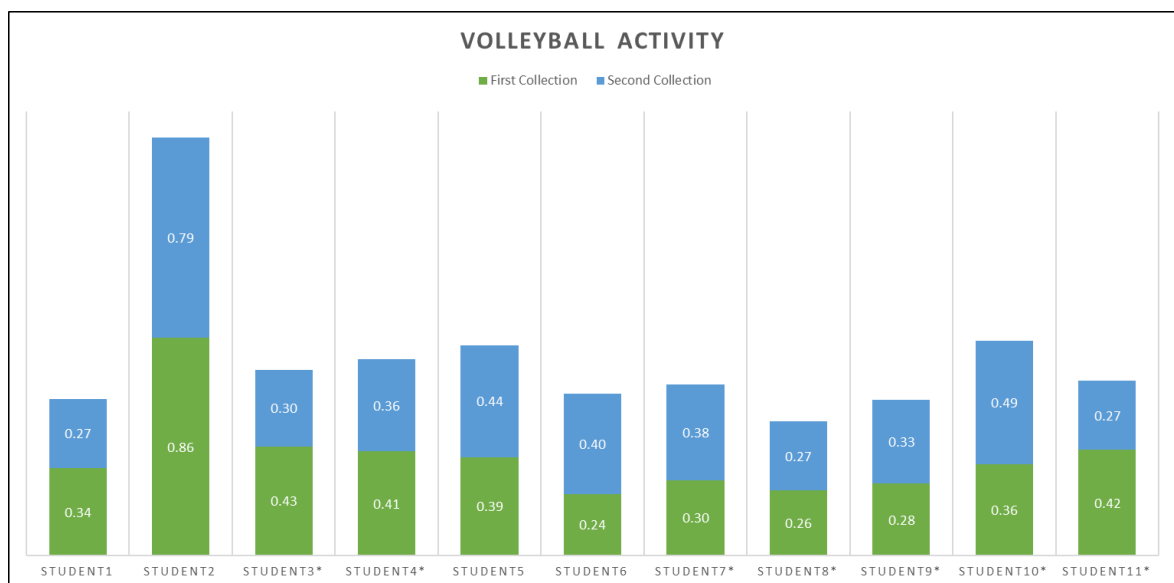


Figure 31 - Volleyball REA for the first two collections, calculated using the average of all the HIRA values collected.

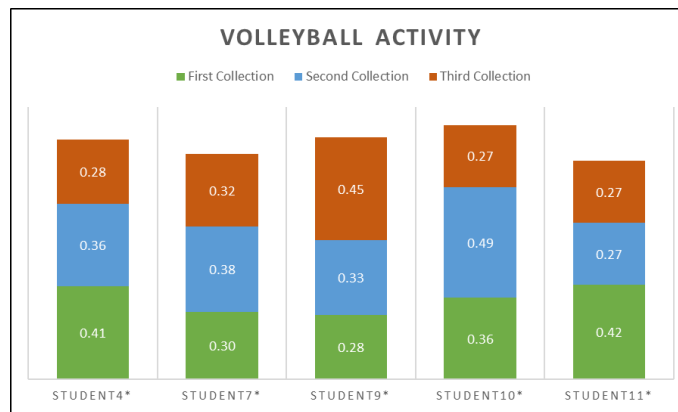


Figure 32 - Volleyball REA for students with three collections calculated using the average of all the HIRA values collected.

Figure 33 represents the REA for the handball, where student 2 equalled the reference value in his second collection, and no other student was able to equal or overcome the reference. As can be seen in Table 11, handball continues to be the second activity with the lowest REA values, and with the third highest standard deviation. Figure 34 displays the chart for students that performed three collections, with no student being able to overcome the reference value.

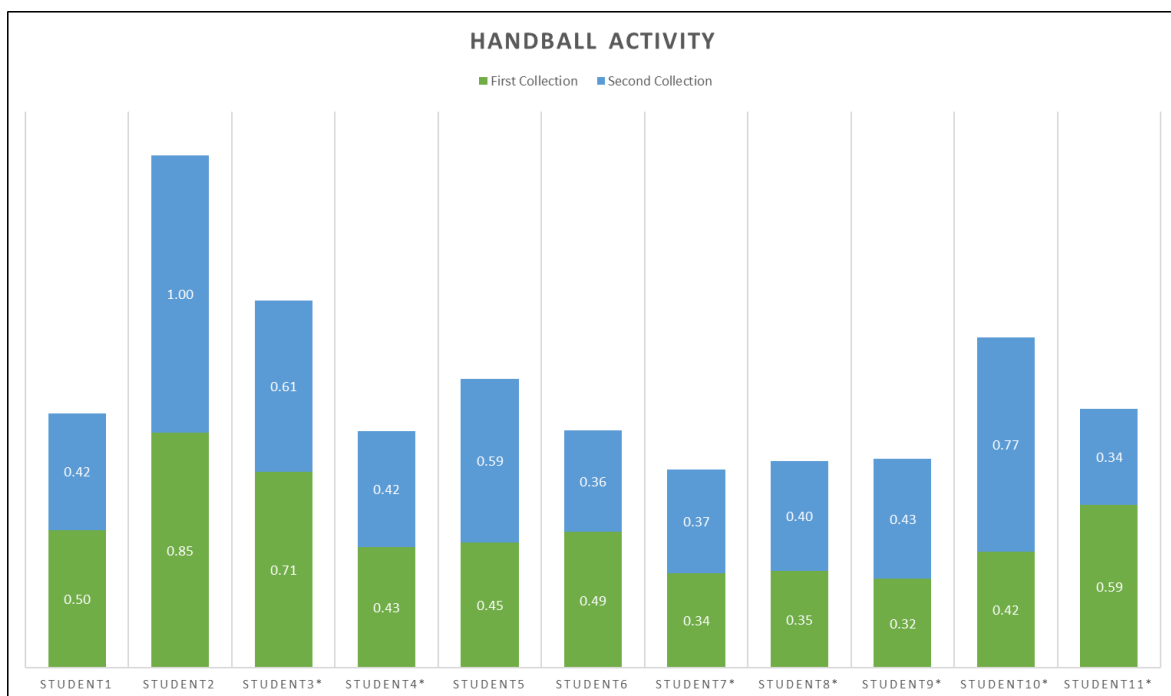


Figure 33 - Handball REA for the first two collections, calculated using the average of all the HIRA values collected.

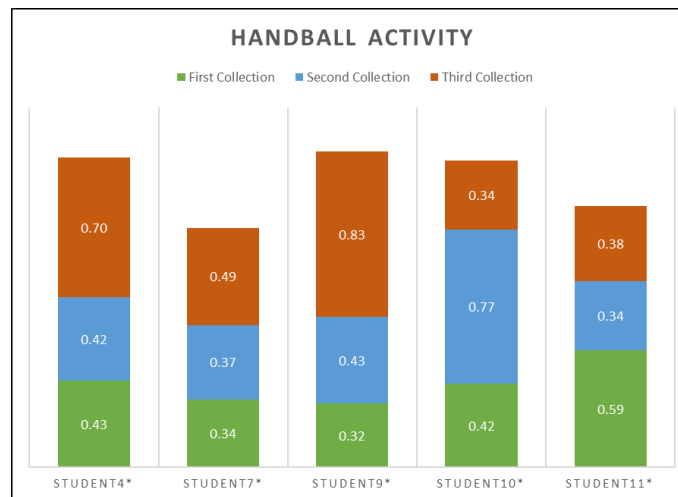


Figure 34 - Handball REA for students with three collections calculated using the average of all the HIRA values collected.

Figure 35 represents the REA for the basketball, where student 2 was near the reference value in both collections, and no other student was able to equal or overcome the reference. As can be seen in Table 11, basketball continues to be the second activity with the highest REA values, and has the second lowest standard deviation of all the activities. Figure 36 displays the chart for students that performed three collections, and no student was also able to equal or overcome the reference.

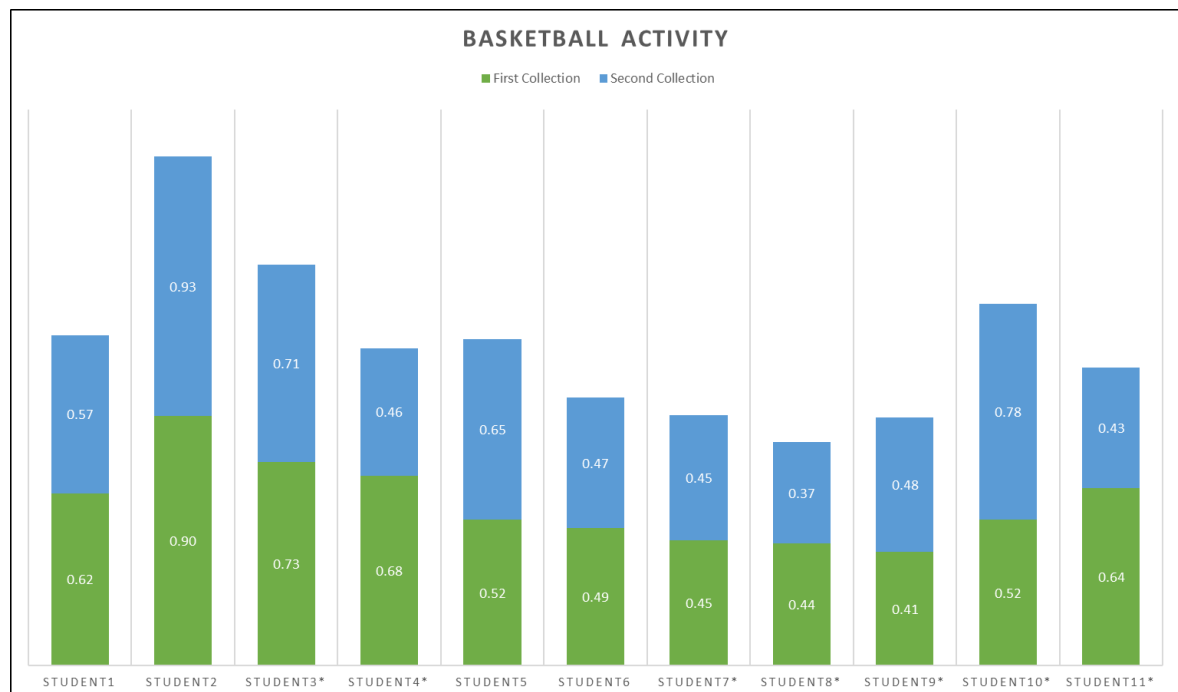


Figure 35 - Basketball REA for the first two collections, calculated using the average of all the HIRA values collected.

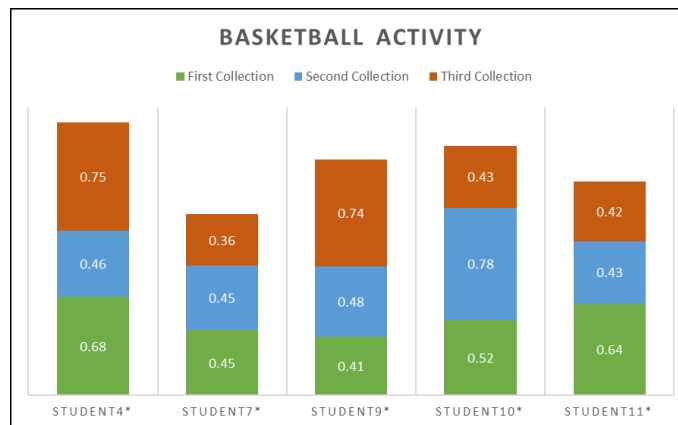


Figure 36 - Basketball REA for students with three collections calculated using the average of all the base values collected.

Figure 37 represents the REA for the futsal, where student 2 overcame the reference on the first collection and was near the reference on the second. No other student was able to overcome the reference during the three collections. As can be seen in Table 11, futsal continues to be the activity with the highest REA values, and as hanball is the third one with the highest standard deviation. Figure 38 displays the chart for students that performed three collections, and no student was also able to equal or overcome the reference.

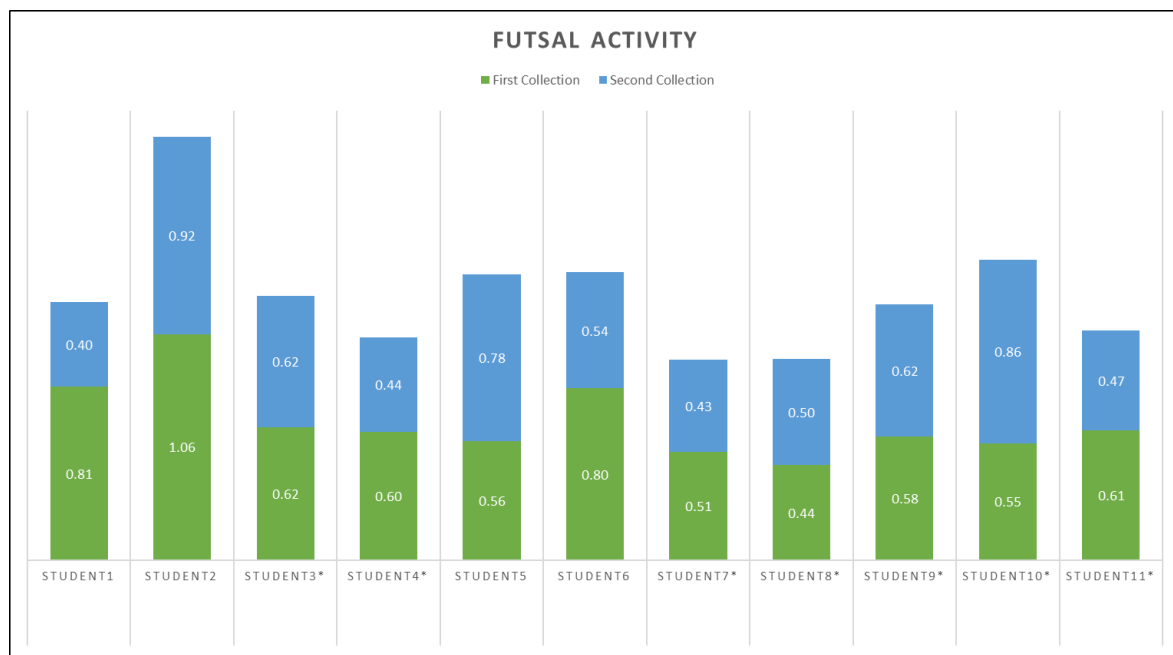


Figure 37 - Futsal REA for the first two collections, calculated using the average of all the HIRA values collected.

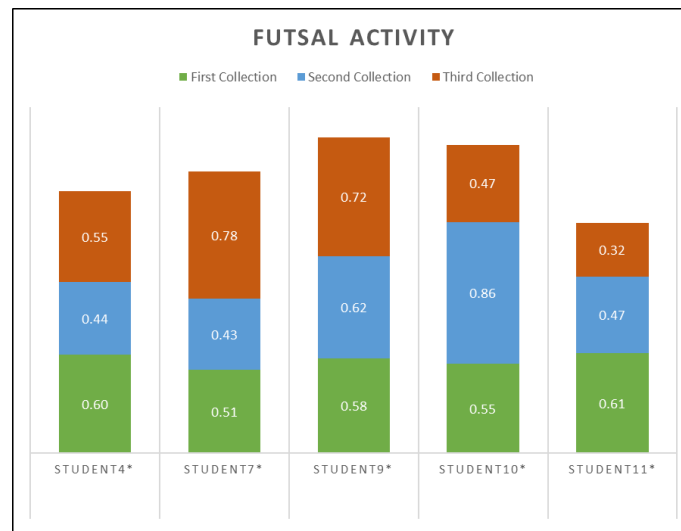


Figure 38 - Futsal REA for students with three collections calculated using the average of all the base values collected.

This methodology is the most robust, but has the problem of not giving the performance of each collection separately, but as a whole, in case the teacher wanted to analyse the performance of all the students during a specific collection it would be more difficult, when comparing with the other two previous approaches, because the REA values are being calculated for all the collections using the mean of the all the HIRA values captured, and in order to use this method, the calibration activity must be performed by the students on all the collections, like in the previous methodology.

The values from the charts (Figures 31-38) can be compared to the activity average, those values are represented in Table 11.

Table 11 - Activities average and standard deviation, using the average base value of all collections.

	Reference	Volleyball	Handball	Basketball	Futsal
Average	1	0.38 ± 0.14	0.51 ± 0.17	0.57 ± 0.16	0.62 ± 0.17

4.5 Remarks

In this chapter it was discussed three different approaches to calculate the REA values, by using the calibration activity value captured during the first collection, using the calibration of each collection, or using the average of all the calibration values. Students 12, and 13 didn't appear on the charts of the three approaches since they only participated in one collection.

The first approach could be used if some students hadn't changed their device used to gather the accelerometry data, which unfortunately didn't happen. In this approach the students only need to perform the HIRA activity on the first collection, which can lead to some students being impaired because of a bad collection, due to physical, motivational or psychological issues.

The second methodology allows the teacher to monitor his students during a determined collection, or all the collections, since some students couldn't keep the same device during all the collections. In this method the calibration activity must be performed on all the collections because the REA values are calculated using the base value captured on each collection. This approach permits the teacher to understand the development of his students, and if they are well physically, psychologically and are motivated, by analysing the charts during the curricular year.

The third methodology allows the teacher to check the overall student's performance, but to check the performance of a single collection the process is less accurate than in the other two methods, as occurs in the second methodology the calibration activity must be performed during all the collections. This approach displays the performance of the students in a more "robust" way, since the performance of the student's activities is compared to the average of the HIRA, granting a more accurate overall performance.

Some students display low REA values, which doesn't mean that they didn't put enough effort, it all depends on the activity performed, as well as how each student tends to have more effort in the activities they like. From the 13 students, 7 changed their smartphone during the collections (Table 4).

5. Conclusion and Future Work

5.1 Major Conclusions

The purpose of the work here presented, is to supplement the student's assessment during the physical education classes, by creating a more objective assessment, in a way, that students who are not able to take advantage of their physical structure or lack of fitness do not feel demotivated/demoralized. The teacher has a really important role to help the students understand the risks of not having an active lifestyle, which may lead to health problems like obesity and other diseases like diabetes, with this solution we hope to encourage the students the practice of regular physical exercise, with the inclusion of technology and a fair metric, which removes the assessment relative subjectivity. The accelerometry data will be provided to the teacher, for decision support in the grading system.

The solution is composed of a set of tools to extract and display the accelerometry data that was captured during the physical education classes. The purpose of this solution is to help the teacher during the evaluation process, by presenting the REA values through charts, individually for each student, where the teacher will be able to compare results obtained, and at the same time corroborate his own perceptions with the captured data, since it requires the teacher to have a familiarity about each student physical condition, to understand if they are performing at their best to guarantee an accurate calibration.

Numerous experiments were done with the collected data, calculating the activities performed, using three different approaches: The first HIRA value captured from the first collection, The HIRA value obtained in each session, and by using the average of all the HIRA values captured. The REA values are displayed in the form of a chart in the front-end application using the second approach, since most of the students changed their smartphones, this way the approach that suit our needs is the second one, since the third one removes a specific collection notion (because is based on the average of all the collections, it's hard to understand what happened during a specific collection). Each student can access their own collected data, and the teacher can check the information of the students he lectures, both can track performance during a specific day, or the overall performance during the curricular year. The data displayed in those graphs is stored in the database.

After the data is uploaded from the smartphones to the server, the teacher needs to access the frontend application and insert the beginning and ending of each activity, to automatically run the JAR file that is stored in the server, which is responsible for calculating the REA values, during the set amount of time introduced by the teacher, after that, the REA values calculated will be inserted in the database.

The REA metric [37], was used due to the heterogeneity of the devices used by the students for the accelerometry data collection, constructing useful results to enable students comparison. The beginning and ending times of each activity is stored in the database, the REA values as well. The frontend application allows the teacher the insertion of the beginning and ending of each activity, in order to calculate the REA values for each activity performed by the students, check the last times inserted, and the REA values that were calculated by using the JAR file that is stored in the server, check REA data by date, class or all the data, and it also has a control panel, where the teacher can add classes, add lecturing classes, add or remove students to a class, and check all the students that are inserted in a specific class. In case a student tries to access their webpage, they can only check information related to them, personal information like name, sex, weight, height, age, body mass index and the graphs that were generated when the teacher inserted the activity times in his user page.

This solution requires a server to store the frontend application, the accelerometry data uploaded by the students, and to perform the data extraction. This is a low-cost solution, since the students used their smartphones to collect the accelerometry data, only needing the purchase of the waist bags to place the devices.

5.2 Future Work

Some improvements can be made to improve the current developed system, some changes can be made regarding the mobile application, where users should also insert a username, email to ease the registry system process. The number of samples that are being captured can also be optimized, by reducing the number of samples without affecting the overall metric performance, this will help reduce the dataset size, and reduce the data that needs to be processed to retrieve the REA metric.

Instead of the smartphones, students could use other devices, such as a fitness band, smartwatch or any other fitness device with an accelerometer incorporated. The advantages of these devices are being low-cost, lightweight, and providing a precise accelerometry data. Even with these devices, there would still be a need for an application able to upload the captured data to the server.

A gamification approach could also be applied, to keep the students interested across the collections. There could be an overall scoreboard, with the class that did best during a semester, curricular year, on each activity performed, there could also be an individual overall scoreboard, but that could lead to bad rivalries between students.

In case the application would be used in more schools, or even by more teachers, the database wouldn't be able to handle the data concurrency, which would be troublesome in case there were more than one teacher trying to submit the beginning and ending of each activity, the JAR file would execute but would be unable to handle the concurrency of writing the REA data on the database.

It would help if more classes could participate in this study, or if there could be protocols with more schools, to increase the number of subjects making the accelerometry collections. This would lead to a bigger number of datasets collected.

The frontend application could allow the comparison between students, the teacher would select a determined number of students and would compare the data between two or more students, or even an average of each activity, to understand which class performed better during a semester or curricular year.

The application could also have a combo box listing all the activities, this way both the students and the teacher could see the charts for each activity separately.

5.3 Concluding Remarks

Due to the limitations of the current evaluation system, the presented solution has the purpose of complementing the student's assessment and grading system during the physical education classes, by using the accelerometer sensor presented in the student's smartphones, to remove those limitations. With the creation of a more objective assessment, where the student's physical characteristics don't matter, we try to motivate the students in a way that those who can't take advantage of their physical structure or lack of fitness can't feel demotivated/demoralized, and at the same time motivate them for the practice of regular physical education activities, alerting them for the risks of not having an active life, which may lead to health problems like obesity and other diseases. At the same time, we want to help the teacher's during a hard process which is the evaluation, with the developed tools to extract and display the accelerometry data captured during the classes, correlating this way technology with physical activity. When that accelerometry data is uploaded to the server, it needs to be processed to retrieve the REA metric values, with the purpose of comparing student's information in a heterogeneous environment.

The three key data reduction criteria didn't present a problem, since we know precisely the valid days in which the collections happened, we also know the wear time and non-wear time of the sensor, since the beginning and ending of each activity were pointed, and since the experiments took place in a close controlled environment.

This metric was validated with the use of three different approaches, unfortunately the sample size was small, only having received data from 13 students, and from those students 2 only made one collection, thanks to these three approaches, different results were obtained as expected. In the first approach, the first and subsequent collections will always be calculated using the same reference, which is the first captured HIRA value, but since 7 of 11 students change their smartphones at least once, there was a discrepancy due to the different sensibility of the devices.

The second approach which displays the more accurate data of the three, uses the HIRA of each collection, this way all the activities of a single collection are compared to the reference of

that same collection, which in this case adapts to the fact that more than half of the subjects changed their devices during the sessions.

Finally, the third one, calculates the average of all the high intensity running activities performed, during all the collections, which can be seen as a continuity, but as the first approach, isn't accurate when a specified collection is observed, since students can be more motivated or better psychologically during a few calibration activities or be demoralized or not as good psychologically and not perform as well as "expected".

From the three approaches, the second one is the one we use on the front-end page, due to the reasons mentioned before, in case there would be no smartphone change, the first approach could be used, but the second one continues to give the best interpretation of what happens during each collection, as well as the overall performance.

The front-end application has a registry and login system, with separate roles for the students and the teachers, with the first ones only being able to track their activities without checking information regarding their colleagues, the teacher can check the information about their students, and perform a series of tasks. All the beginning and ending of each activity, and the calculated REA values are stored on the database, and are then generated into charts, thanks to the google charts [68].

Sensor data offers an easy and great prospect for the creation of new solutions that can help people from the simplest daily life activities to some of them more complex, such as walking, cooking, remote health monitoring, navigation, entertainment, and others, to improve the overall people's quality of life, and quality of service.

6. References

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