# Smart Gait

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## ABSTRACT
This paper presents a new gait and stationary assistant based on sensing and providing feedback through the use of of-the-shelf devices, like smartphones and smartwatches. Ataxic and healthy individuals' inertial data was collected with these devices by following a protocol based on the Timed 25-Foot Walk standardized assessment test. This data was analyzed, synchronized and used to build Neural Network models able to identify balanced and imbalanced moments with an accuracy of 99.18%, 98.61% and 98,04%, respectively, at rest, walking, and both at rest and walking. In addition, these models were developed to be able to perform real-time inferences with these devices and a data synchronization algorithm was developed. From these results, this feedback system was considered to be promising in identifying imbalances with high accuracy, therefore not disturbing the users in balanced conditions.

### Author Keywords
Ataxia; postural oscillation; smartphone; smartwatch; accessibility; machine learning.

### ACM Classification Keywords
Neural nets.; Portable devices; Wireless communication;

## INTRODUCTION
Ataxia describes a group of disorders that affect muscle movement coordination, including gait, balance, and speech. It may be caused by damage to the cerebellum, a part of the brain, or to other parts of the nervous system. Although there are many types of ataxia, they can be separated in two broad categories:

- **Cerebellum ataxia** - where the symptoms develop slowly and progressively through the years due to faulty genes, that a person inherits from their parents, or as the result of a trauma, like a stroke, multiple sclerosis, or other problems that damage the brain;
- **Sensory ataxia -** where dysfunction of the spinal cord's dorsal columns or the various parts of the brain that receive positional information causes loss of proprioception, the loss of sensitivity to the positions of joint and body parts.

Ataxic gait is defined by a wide stance and an irregular stride. However, each of these categories present different characteristics. Individuals with the former often stagger and resemble an inebriate person, while with the latter display an unsteady stomping gait with heavy heel strikes.

These individuals are assessed by specialists on appropriate scales according to their movement capabilities. Though, these assessments can be subjective, as different specialists can make dissimilar observations. Also, this pathology is irreversible, since there are no pharmacology treatments or others that allow its cure. Physiotherapeutic treatments have proven to be effective on delaying its progression and extending these individuals' ability to walk independently for a longer period [13]. Nevertheless, these treatments are associated with high monetary costs and long travels to specialized clinics [12]. Consequently, many scientific studies have been done to minimize these barriers.

However, the biggest adversity that these individuals face is related to their **inability to control voluntary movements** which leads to an unstable and imbalanced gait, and to a major risk of falling and independency loss. Therefore, research facing this issue has also been done. Thus, the utilization of force and inertial sensors to provide feedback and help individuals controlling their voluntary movements has been considered. Though, most of these systems were developed using expensive and hard to find technology. Not only that, but the few studies that focused on using smartphones, only took into account situations where the user was standing at rest.

The technological advancements, namely, the integration of inertial sensors and high processing and storage capabilities, in cheaper and more accessible devices, like smartphones and wearables, allows the characterization of their users' movement [1] and to develop systems able of providing assistance in situations such as those mentioned above. Furthermore, these devices are increasingly part of people's daily lives, having been estimated that in 2016 there were about 2 billion and 102 million smartphones and wearables users, respectively. Therefore, it is becoming more and more common to use these devices simultaneously and in different parts of the body, which makes it possible to take advantage of them and improve the accuracy of the systems developed.

Considering this, we propose a solution to leverage the huge amount of inertial data that is already being generated on off-the-shelf devices and provide non-disruptive yet helpful feedback on controlling the equilibrium and preventing impending falls. **Hence, we developed a prototype composed by a smartphone and a smartwatch application that allows to sync and analyze the inertial**

**measurements provided by their sensors and to provide feedback if the user is in an imbalanced situation.**

To make this possible, we started by collecting data of both healthy and ataxic individuals while using the smartphone on the right pocket and the smartwatch on the left wrist. Afterwards, we labelled each instance collected accordingly with the user's balanced or imbalanced state and generated different datasets by using not only the data collected by each device, but also the data synchronized between them. These datasets were merged to be representative of the user current activity, namely, at rest, walking and both at rest and walking. We have also applied mathematical and statistical operations to generate new derived measures to these datasets. Then, different Machine Learning algorithms were assessed in each dataset. Being observed that the best results were obtained by feeding the unprocessed and synchronized datasets to a Multilayer Perceptron Neural Network. **These models presented an accuracy of 99.18%, 98.61% and 98,04% and an imbalanced a false negative percentage of 1%, 1%, 2%, and a false positive percentage of 4%, 16%, 15%, respectively, at rest, walking, and both at rest and walking.**

After that, we added these models to the smartphone application and developed an algorithm capable of synchronizing, in real-time, the inertial data produced by itself and sent by the smartwatch, as well as, of identifying if the user is walking or at rest and choosing the correct models to classify the synchronized data. After each classification, the smartphone was also able of sending the result obtained to the smartwatch application, so that it could provide haptic feedback if the user was in an imbalanced state.

## RELATED WORK

As mentioned before, scientific research is being done to ease the access to physiotherapeutically therapies, as well as to evaluate the effects and the progression of this disorder. Thus, these studies focus on sensors to collect inertial data, to assess postural instability, and on real time methods to improve postural stability.

LeMoyne et al. [1], stated that the technological advances in computation power allow to develop systems able of measuring and calculating in real-time human movement biomechanical parameters. This is possible by using Inertial Measurements Unities (IMUs), which have accelerometers, gyroscopes, and magnetometers. Inertial systems like the Xsens and Sensor Tag have been used by Hanakova et al. [2] and LeMoyne et al. [3], respectively, to analyze the inertial data provided by these devices and develop methods to distinguish ataxic and healthy individuals. To do this, the former evaluated standing 3-D movements using a method based on the volume of confidence ellipsoid (VE) of the set of points obtained by plotting three accelerations against each other. Whereas the latter collected the roll, yaw, and pitch axis of the gyroscope to train a multilayer perceptron neural network able of distinguishing these individuals while walking. These authors stated that the usage of this sensors together with the techniques contemplated are very sensitive to changes in stability and may offer the potential to enhance clinical diagnostic acuity and conceivably prognostic foresight. Besides these devices, IMUs can also be found in smartphones, tablets and wearables, like smartwatches and have already been considered by LeMoyne et al. [1] and Lee et al. [4].

On the other hand, Redd and Bamber [10] studied the most effective sensory methods of feedback on modulating the gait of study subject. These authors verified that both visual and vibrotactile methods resulted in significant changes in gait asymmetry. However, the greatest difficulty on developing feedback systems is setting the devices needed on the human body, as they can generate difficulty of acceptance due to their size and weight. Therefore, different devices and body parts have been considered.

The research done by VanderHill et al. [8] and Afzal et al. [6], on passive feedback stemming from the stabilizing effect of holding an object on upright posture provided similar results. Therefore, the former stated that this stabilizing effect, that has been demonstrated in a variety of settings, is due to focusing attention on motor task performance.

As stated by Hegde et al. [5], post-stroke patients tend to favor the affected extremity, reducing the time and percentage of individual support of the limb in a full gait cycle. Which can be seen as pronounced limp during walking. Therefore, pressure sensors in insoles have, not only, been considered by these authors, but also by Afzal et al. [7]. In these studies, the authors used pressure sensors to analyze gait symmetry and provide vibrotactile feedback on the feet and on the lower limbs, respectively. The utilization of the systems developed by these studies' participants resulted in a more symmetrical gait.

Additionally, Mazilu et al. [9] compared the detection accuracy of Freezing of Gait events in Parkinson individuals with sensors placed in the wrists and ankles. Besides increasing the amount of false alarms and increasing the latency of detection, placing the sensors on the wrists improved the comfort of the participants.

Every system developed in the studies analyzed showed positive results, being able to influence postural equilibrium of ataxic individuals independently of its type. However, most of these studies were performed with few participants and in a limited amount of time, therefore it was not possible to verify the long-term effects of these systems utilization. Furthermore, these studies focused on laboratory settings with difficult to find devices and did not considered walking imbalances that occur independently of the type of ataxia. Thus, in this document, a solution based on collecting inertial data from off-the-shelf devices, like smartphones and smartwatches, and providing feedback in case of imbalances while at rest or walking is presented.

## DATA COLLECTION ORCHESTRATION

To analyze the data generated by these individuals, we developed a prototype composed by a smartphone and a smartwatch that allowed the collection of inertial data in moving and stationary tasks.

### Hardware analysis and selection

To select the appropriate smartphone, the most popular ones were analyzed, having been verified that both Android and iOS smartphones have inertial sensors like accelerometers, gyroscopes, and magnetometers. Furthermore, these smartphones also provide processed signals that aim to reduce these sensors' bias, namely, linear acceleration, gravity acceleration, attitude, rotation rate, and calibrated magnetic field. In comparison with the Androids, the iOS smartphones have a fixed sensor reading frequency of 100 Hz while the Androids' frequency is dependent on the device. Therefore, an iPhone 6 Plus was selected, as this device allows the use of the full range of frequencies available, while still being compatible with every other device with the same operative system.

After choosing the smartphone, we analyzed the smartwatches available on the market, having been verified that the Android ones are not compatible with the chosen smartphone, but the Pebble's smartwatches are. However, this company has been bought by Fitbit and their smartwatch production has been stopped. Therefore, we have chosen the Apple Watch has it is compatible with the iPhone and has the same sensors and processed signals as the later.

### Data collection requirements

The tasks executed were based on the Timed 25-Foot Walk standardized assessment test, as previously considered by LeMoyne et al. [3]. This test consists in traversing a hallway with 25 feet in both directions (Figure 1). To assess the participants' balance in standing tasks, we also considered a 5 second resting phase after the walking tasks completion. To be able to better analyze the participants' posture we have decided to film the execution of these tasks. Therefore, a video camera should be placed on the frontal plane of the users, as we considered that this plane allows a complete visualization of the participant in every moment of the exercise. Moreover, it was defined that participants should wear the smartphone in their right trousers pocket and the smartwatch on their left wrist.

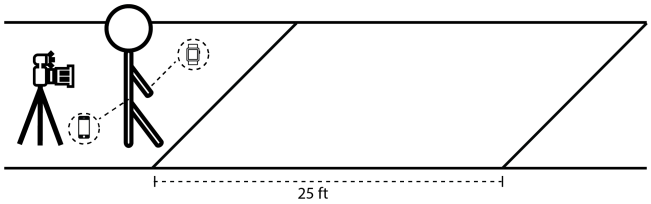



**Figure 1. Data collection setup.**

### Data collection applications

In order to collect data during these tasks, we implemented an application for the selected devices. This application, was not only able of reading and persistently storing inertial data, but also to guide the participants in carrying out the tasks. To do this, we defined a collecting protocol that included three different stages, namely, walking outbound, walking return, and rest. So that the devices are synchronized during the execution of the tasks, both of them should follow this protocol and start each task at the same time. The smartwatch was considered to be the most accessible device, as it is located on the user's wrist. Therefore, this device should be the starting point to initiate the collecting procedure.

Hence, as soon as this procedure is started, the smartwatch should execute a handshaking phase with the smartphone. In this phase, the smartwatch calculates a new timestamp about 5 seconds after the actual time and sends it to the smartphone. The latter, when receiving this message should verify if the timestamp is still valid, in other words, if due to latencies the message got delayed and the timestamp as already passed. In case it is valid, this device should send a confirmation message to the smartwatch that it is available to start the collecting procedure. After this phase, both of the devices should set a countdown to the agreed timestamp and inform the users with a visual and voice indication of the remaining seconds to start the task.

$$timeLimit = 1.5 * numberOfGaitCycles \quad (1)$$

As these devices should guide users on the tasks execution, they need to be able to understand their completion. To do this, we used the pedometer sensor of these devices, however we found that they provided different measures which contributed for the devices to be out of sync. Because of that, we verified that the Apple's Research Kit framework did this verification with the Equation timeLimit $= 1.5 * numberOfGaitCycles \ (1)$. Therefore, we calculated that in average a male would need 10 steps to complete 25 feet, while a female would need 11 steps [11]. Moreover, we considered that the walking tasks would be completed if the users executed 5 complete gait cycles. This way, when starting a new task a timer with the time limit calculated with the Equation timeLimit $= 1.5 * numberOfGaitCycles \ (1)$ is set, if the user is executing a walking task, or with a 5 second time limit, if it is a resting task.

After each task completion, the devices should check if there are any tasks left to do. If there are the smartwatch should execute the same handshaking procedure mentioned earlier. However, it should create a new timestamp with 1 second difference, as this interval was proven to allow the exchange of these messages. This phase will allow to guarantee that both devices are in sync and ready to initiate a new task, while avoiding losing data in the process. On the other hand, if there are no more tasks left, the smartphone should start persistently saving the data collected, while the smartwatch should transfer the data to the smartphone so that it can also be saved.

## INERTIAL DATA COLLECTION

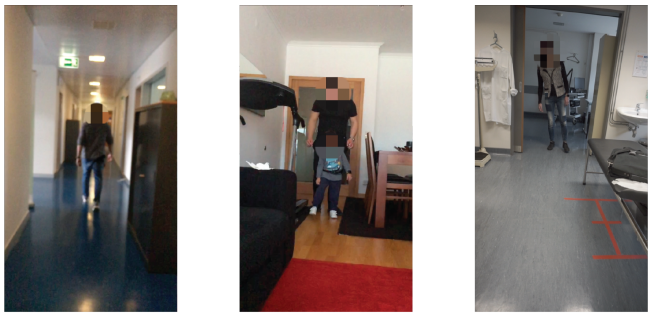
Due to the size of the smartphone, we developed an attachment system to be used in participants in which the smartphone would not fit in the pocket so that we could fix the device in the same region (Figure 2). Furthermore, every task was recorded with the authorization of the participants.

Data for 13 participants, 7 ataxic and 4 healthy, was collected, resulting in 10400 stationary and 19653 moving instances, for which moments of imbalance were manually annotated. To do this, three different data collecting sessions were performed.

**Figure 2. System of attachment of the smartphone to the body.**

### Data collection from healthy individuals

As previously mention, data from 4 healthy individuals (3 male and 1 female) was collected (Figure 3 (a)). This session took place on the campus of *Instituto Superior Técnico* in Taguspark, on March 20, 2017. The participants were between the ages of 22 and 24 years old. Each of these individuals successfully executed three times the tasks planed, as we have noticed that fatigue would not influence their performance.



(a) (b) (c)

**Figure 3. Data collection sessions. (a) Healthy individuals at *Instituto Superior Técnico*. (b) Ataxic child in Gaia, Portugal. (c) Ataxic individuals in *Hospital Senhora da Oliveira*, Guimarães, Portugal.**

### Data collection from an ataxic child

After collecting data in healthy individuals, we contacted the father of a male ataxic child that had showed interest in participating on this research. Therefore, on April 2, 2017 we were able to do a collecting session at their place in Gaia, Portugal (Figure 3 (b)).

This child had hereditary cerebellar ataxia and presented difficulties on controlling fine movements and a severe postural control difficulty in static and dynamic conditions. Due to these conditions, this child was very dependent on their parents and needed help on doing the proposed tasks. Besides that, we were not able to position the smartphone on his pocket nor use the system developed to fix the smartphone on his leg, therefore we decided to use it on the lumbar region.

While executing the tasks, we observed that the child had an extreme difficulty on performing the walking tasks reaching the limit of near fall shortly after the first steps. On the other hand, we verified that he was able execute the resting phase more easily, while still showing difficulties in postural control. Nevertheless, the child was able to perform the tasks four times.

### Data collection from ataxic adults

In order to collect data in ataxic adults, many institutions were contacted, having been possible to collaborate with the neurology department of the *Hospital da Senhora da Oliveira*, Guimarães, Portugal (Figure 3 (c)).

This session took place on May 10, 2017, having been gathered 6 ataxic patients (2 male and 4 female). These patients presented sporadic cerebellar ataxic as result of strokes or multiple sclerosis. Furthermore, two of these individuals were not able to walk independently, requiring unilateral aid of a crutch.

Due to the space requirements of the tasks planned, the first 3 participants performed them in a hospital hall. Yet, because of the increasing number of people on that area of the hospital, we needed to move. This way, we have first moved to an office that didn't have the space required and then to other that met these tasks' requirements. However, we verified that this office had large objects that allowed the participants to uphold in case of imbalances, although they did not interfere with the walking path. While, these objects helped the patients not falling, they might have influenced the data collected. Each of these participants executed the tasks six times, since we have noticed that fatigue could also make an impact on postural control.

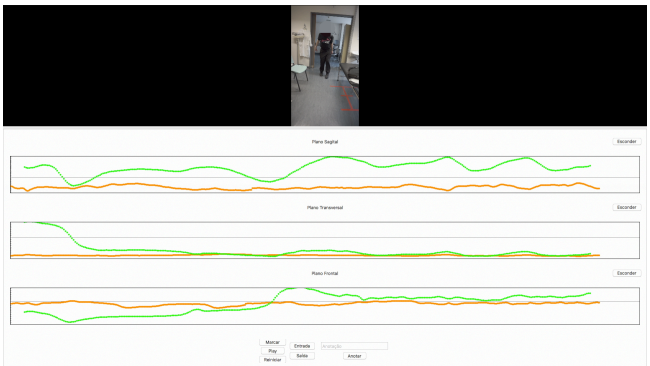



**Figure 4. Manual classification and visualization tool.**

### Manual classification and visualization tool

To ease the annotation process, a tool that allowed the visualization of the data collected, together with the synchronization of the high-speed video recorded at the time of the data generation was developed (Figure 4). Thus, the videos recorded together with the datasets of each

task and from both devices were imported to this tool. Then, each data instance was annotated from a set options, namely, 'balanced', 'imbalanced' and '?'. The latter meaning that the instance should be removed.

The annotated data from each device was synchronized and merged to assemble different datasets depending on the user activity, namely, at rest, walking and both at rest and walking. Non-synchronized data from each device was also assembled based on these activities. Additionally, these datasets were processed by using different mathematical and statistical operations. Hence, both unprocessed and processed datasets were generated not only from the synchronized instances, but also from each device.

## CLASSIFICATION OF IMBALANCED SITUATIONS

The datasets generated previously allowed to assess different supervised Machine Learning (ML) algorithms, namely, Decision Trees (DTs), Support Vector Machines (SVMs), and Neural Networks (NNs). These algorithms were selected as they are able to handle complex datasets with a high number of entries, having techniques to avoid data overfitting and executing classifications in a short amount of time.

Hence, different platforms that allowed to test these algorithms' performance with the collected data were analyzed, having been verified that the Weka application not only supported these algorithms, but also allowed to analyze and modify datasets, as well as provided different testing techniques and a very intuitive visual interface. Moreover, this tool provides a multitude of performance parameters that can be analyzed to measure the quality of the models generated.

As these algorithms require to be parametrized and tuned to provide the best results, we compared their performance using a multi-search technique, where different combinations of parameters are tested, in order to find the ones that perform better. Furthermore, a k-fold cross validation technique was used to evaluate how the models generated would adapt to unseen data.

As it was previously stated, Weka provides a set of performance measures for each model generated. In Table 1, it is presented the attributes considered to be the most important on analyzing this particular problem, namely, accuracy and the ratio of false negatives and positives. Therefore, in these models, we aim to maximize their accuracy, so that we can correctly classify the highest number of instances possible. But, also to minimize false negatives and positives ratio, as we want to avoid alerting the users that they are imbalanced when in fact they are balanced (false negatives) and to avoid missing imbalances and impending falls (false positives).

In the same table, it is possible to observe the results achieved while using the datasets that provided the best performance on training these algorithms, namely, the unprocessed and synchronized datasets. We observed that the SVM algorithm did not perform as expected, having a high ratio of false positives and low accuracy compared to the other techniques. In the other hand, the Multilayer Perceptron Neural Network and the Random Forest, which is an implementation based on a multitude of DTs, performed very similarly. Even though the Random Forest algorithm showed slightly better results, we considered that the Multilayer Perceptron would be a better option to this problem as it is able to perform classifications in a very short amount of time.

The models obtained were able to classify the users balance at rest, walking and both at rest and walking presenting an accuracy of 99.18%, 98.61% and 98.04%, a false negative percentage of 1%, 1%, 2%, and a false positive percentage of 4%, 16%, 15%, respectively. These models correctly classified most of the instances tested and yielded a low percentage of false negatives and positives, which, respectively, means that few balanced and imbalanced conditions were wrongly classified. Based on those results, we developed an application capable of synchronizing, in real-time, the data collected by the devices used, as well as classifying the user's equilibrium and providing feedback in imminent imbalances and falls.

| Classifier | Activity | Accuracy (%) | False Negatives Ratio | False Positives Ratio |
|---|---|---|---|---|
| SVM | Rest | 92.82 | 0.07 | 0.45 |
| | Walking | 94.72 | 0.05 | 0.82 |
| | Both | 93.04 | 0.07 | 0.76 |
| Random Forest | Rest | 99.85 | 0.002 | 0.008 |
| | Walking | 99.76 | 0.002 | 0.03 |
| | Both | 99.75 | 0.003 | 0.02 |
| Multilayer Perceptron | Rest | 99.18 | 0.01 | 0.04 |
| | Walking | 98.61 | 0.01 | 0.16 |
| | Both | 98.04 | 0.02 | 0.15 |

**Table 1. Results obtained in the use of several supervised ML algorithms in the classification of the unprocessed and synchronized datasets.**

## REAL-TIME CLASSIFICATION

To be able to identify in real-time these individuals' equilibrium state we developed an application for each of the devices used previously. Due to the nature of each of device, both of these applications had different responsibilities. The smartwatch provided a way to start the real-time classification process and to deliver haptic and sound feedback to the user, while collecting data and sending it to the smartphone. The later was responsible for synchronizing the data received by the former, classifying it and sending the result to the smartwatch. Furthermore, the

smartphone also stored the synchronized data, so that we could analyze it afterwards.

### In device classification

To develop an application capable of classifying the inertial data read on these devices, we needed to add the models generated previously to them. However, Weka did not allow to export these models. Therefore, we analyzed different libraries that allowed to train a Multilayer Perceptron Neural Network and perform on-device classifications.

At first, Swift-ML was the only library available that met these requirements. However, while developing this application, the library Core ML was made public by Apple, the company responsible by creating the devices used. Therefore, we developed models for the datasets chosen using both libraries, in order to choose the one that provided the bests results.

These libraries were configured with the parameters obtained in Weka, but the results obtained were far from similar. Because of that, we executed the same Multi Search technique used in Weka until we achieved the best results possible. However, these models presented a lower accuracy compared to the ones obtained in that tool, which can be due to different implementations of the algorithm used or to internal optimizations that aren't replicated on these libraries.

| Classifier | Activity | Accuracy (%) | False Negatives Ratio | False Positives Ratio |
|---|---|---|---|---|
| Weka | Rest | 98.60 | 0.01 | 0.16 |
| | Walking | 99.18 | 0.01 | 0.04 |
| | Both | 98.04 | 0.02 | 0.15 |
| Swift-AI | Rest | 94.29 | 0.02 | 0.48 |
| | Walking | 95.99 | 0.03 | 0.17 |
| | Both | 90.56 | 0.03 | 0.58 |
| Core ML | Rest | 96.65 | 0.03 | 0.19 |
| | Walking | 97.66 | 0.02 | 0.08 |
| | Both | 95.50 | 0.04 | 0.18 |

**Table 2. Comparison of the results obtained in libraries compatible with iOS and Weka.**

Even so, we verified that the Core ML library provided the best results, having been achieved an accuracy of 96.65%, 97.66% and 95.50%, a false negative percentage of 3%, 2%, 4%, and a false positive percentage of 19%, 8%, 18%, respectively, at rest, walking and both at rest and walking (Table 2).

### Synchronizing data packets

As the synchronized datasets provided the best results when classifying imbalances, an algorithm to execute this process in real-time was developed. Even though the Core ML library allows to do classifications in both devices, we have chosen to do this process in the smartphone as it has more processing power and better storage capabilities, therefore the smartwatch needs to send the inertial data read to the smartphone, so that the later can execute the synchronization and classification process, and wait for this classification to provide feedback to the user.

To do this, wireless communications latencies were taken into account, therefore it was verified that these are dependent on the number of messages exchanged between the devices and size of each message. Hence, to reduce the number of messages exchanged, we decided to group data in packets by a certain amount of time. However, we had to have in mind that, by doing this, the size of the messages increases and that the packets need to reach the smartphone in a reasonable amount of time, in order to still be relevant.

To synchronize these packets, we began by ensuring that the classification process started at the same time in both devices. To do this, the handshake phase mentioned previously, where the smartwatch calculates a future timestamp and sends it to the smartphone, was performed. When receiving this message, the latter should verify if the timestamp is still valid and send a message back to confirm that it is available to start this process. This timestamp should allow the exchanging of these messages and the preparation of this task in both devices. After that, the devices should schedule the start of the tasks to the timestamp agreed. By doing this and grouping data with a defined interval of time, we ensure that, in any point in time, both of the devices have created the same number of packets. Therefore, these packets can be identified with a numerical attribute that is incremented accordingly to the creation of new packets.

After each interval of time, the smartwatch should send the packet created to the smartphone. When receiving this packet, the smartphone should compare its identifier with the last packet generated on this device and decide if the packet is on time or is late. In the first case, each entry of a packet should be merged with another one of the corresponding packet. This should be done by comparing the timestamps of each entry, in order to merge entries with the smallest possible timestamp difference. In case the packets arrive late, they should be dropped.

### Detecting current user activity

As we developed different classifications models based on the user activity, namely, at rest, walking, and both at rest and walking, we needed to be able to identify the current activity in real-time in order to use the appropriate classifiers. Therefore, we verified that these devices sensors' framework provide access to a set of possible activities that a user could be doing. These are stationary, walking, running, automotive, cycling, and unknown. On this framework's documentation, it is stated that if the device is not capable of clearly identifying one of the

options, more than one can be set as active. Because of this, we decided to handle only the stationary and walking activities, but also that these tasks always start as the former and the current activity can only change when the device is able to identify a single activity.

### Synchronization algorithm performance assessment

Due to the latencies mentioned before, we analyzed different collecting times and verified that by grouping data during 0.3 and 0.4 seconds (s) we are able to synchronize successfully 66.14% and 78.06% of the packets, respectively (Table 3). However, both of these options result in different roundtrip times, the former takes in average 0.87 s, while the latter takes 1.16 s. To choose between both of these times, we analyzed the videos recorded on the first stage of data collection and verified that since the start of an imbalance till the individuals re-establish their equilibrium it takes in average 1.28 s. Therefore, even though there are less packets successfully synchronized, we decided to group this packets in 0.3 s as we would be able to do more classifications during an imbalance.

| Time of data collection | % of successful syncs. | Round trip time since packet is formed (s) | Round trip time since first entry is read (s) |
|---|---|---|---|
| 0.2 | 23.48 | 0.79 | 0.99 |
| 0.3 | 66.14 | 0.57 | 0.87 |
| 0.4 | 78.06 | 0.76 | 1.16 |

**Table 3. Assessment of the synchronization process using different data collection times.**

### Assessment of the solution developed

To assess the solution developed, we weren't able to establish contact with ataxic individuals. Therefore, we collected data of three healthy individuals, one male with 24 years old and two females with 24 and 74 years old.

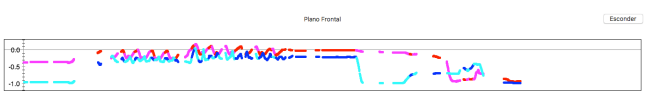



**Figure 5. Visualization of the frontal plane of the gravity acceleration signal classified in real-time by the smartphone.**

Afterwards, we updated the tool developed to visualize and manually annotate data, to support the datasets collected in this stage and to calculate statistical measures.

These measures included the percentage of well identified activities and well classified instances, but also the percentage of well classified instances if the activity had been correctly identified, and the percentage of balanced instances by activity.

As analyzed previously, due to wireless communication latencies, some packets fail to be synchronized. When importing the data classified in real-time to this tool we were able to identify these moments by visualizing the gaps present in between the signals (Figure 5). Furthermore, we were able to manually annotate both the expected classification and current activity so that we could compare with the results provided by this solution.

In average, we verified that this system was able to correctly identify the current activity of 48.78% of the instances, while correctly classifying 72.97% of them. Even though, we verified a low percentage of current activities well identify this did not reflected on the percentage of correctly classified instances. Moreover, we examined that the percentage of instances correctly classified if the activity had been correctly identified was of 100%, 97.95%, and 99.99%, with a percentage of balanced instances of 99.03%, 98.28%, and 99.57%, respectively, at rest, walking and both at rest and walking (Table 4).

| | | Average (%) |
|---|---|---|
| **Well identified activities** | | 48.78 |
| **Correct Classifications** | | 72.97 |
| **Correct classifications for right activity** | Rest | 100 |
| | Walking | 97.95 |
| | Both | 99.99 |
| **Balanced instances** | Rest | 99.03 |
| | Walking | 98.28 |
| | Both | 99.57 |

**Table 4. Results obtained using the solution developed for real-time classification**

Hence, we verified that these classifiers provide a high percentage of correctly classified instances. However, the current activity identification does not meet expectations. To solve this, we could give a higher importance to the classifier of both activities since we have seen that it is able to classify the users' equilibrium with high accuracy.

## CONCLUSIONS

The presented results are very promising, as we were able to achieve a very high percentage of accuracy and a very low percentage of false negatives and positives. Therefore, these classifiers will not disturb the users in balanced conditions, while still identifying imbalanced situations. While the approach is sound, some technical hurdles still need to be overcome, namely the latency in Bluetooth data transfer between smartwatch and smartphone, and some sensitivity to the placement and orientation of the devices on the user. Hence, a better data processing technique that allowed to reduce the latency and freely position the devices without losing data granularity should be considered.

## ACKNOWLEDGMENTS

I thank all the participants of this research, especially the parents of the ataxic child and the neurology department of

the *Hospital da Senhora da Oliveira*. I would also like to thank my thesis supervisors that were always available to help and give insightful feedback.

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