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Characterize a Step Using Machine Learning

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Abstract

Most of pedestrian inertial navigation system estimates displacement based on the integration of inertial sensors measurements. However, due to low-cost sensors and pedestrian dead reckoning inherent characteristics these systems provide huge location estimation errors. To suppress some of these limitations we propose a pedestrian inertial navigation system based on low-cost sensors and on information fusion and learning techniques. The proposed system introduces a step characterization module that characterizes the step according to the activity that the pedestrian is performing. This module performs three characterizations: terrain, direction and length. Thus, in this work are presented and evaluated several machine learning approaches that perform the terrain characterization. The inclusion of this machine learning module led to a significantly better performance of the pedestrian inertial navigation system.

Keywords: *Pedestrian Inertial Navigation System, Indoor Location, Learning Algorithms, Neural Network, SVM, Information Fusion*

1. Introduction

In ubiquitous systems location information is very important to provide richer, more productive and more rewarding user experiences. This information can be explored to improve life quality since emergency teams (fire-fighters, military forces [1] and medics) can respond more precisely if the team members location is known, tourists can have better recommendations [2], the elderly can be better monitored [3] and parents can be more relaxed with their children in shopping malls [4].

The major limitation of these systems is related to retrieving individual's location, which nowadays is based on a GNSS (Global Navigation Satellite System), restricting the use of these systems to environments where GNSS signals are available. However, GNSS signals are not available inside buildings, in urban canyons, in the underground, underwater and in dense forests. Consequently location-aware applications sometimes cannot know the user location. Therefore, developing complementary localization technologies for these environments would unleash the use of many applications as presented above.

There are already some proposed systems that retrieve location in indoor environments. However, most of these solutions require a structured environment [5-6]. Therefore, these systems could be a possible solution for indoor environments, but are unfeasible to be implemented in a dense forest or in urban canyons. To suppress structured environment limitations, a Pedestrian Inertial Navigation System (PINS) can be used. Typically, a PINS uses accelerometers, gyroscopes, among other sensors, which information is used by an algorithm that involves three phases: (i) step detection, (ii) step length estimation, (iii) and heading estimation. Thus, it continuously estimates via dead reckoning the

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position and orientation of a pedestrian. These sensors are based on MEMS (Microelectromechanical systems), which are tiny and lightweight sensors, making them ideal to integrate into the person's body. Unfortunately, large deviations of inertial sensors can affect performance, so the PINS main challenge is to correct the sensors deviations. An abroad overview over the current state of the art is presented in Section 2.

In the previous works of the research team, the step detection was improved by using an algorithm that combines an accelerometer and force sensors placed on the pedestrian's foot [7]. This approach led to better results [8] on the estimation of the pedestrian displacement. However, it still exists an error of 0.4% in step detection and an error of 7.3% in distance estimation.

Considering the works that are being developed in other INS (Inertial Navigation System) areas, but applied in different contexts, we have found that PINS accuracy can be improved using more than one IMU (Inertial Measurement Unit) placed on different regions of the human body, combined with information fusion and learning techniques. Based on the typical PINS algorithm, we have introduced another phase, step characterization, which characterizes the step according to past data. This characterization is applied to limit the typical error growing of PINSs.

Information fusion is a multi-disciplinary research field with a wide range of potential applications in areas such as defense, robotics, automation and pattern recognition. During the past two decades, extensive research and development on multiple sensor data fusion has been performed for the Department of Defense of the United States of America [9]. This subject has been and will continue to be an ever-increasing interest field in research community, where it is intended to develop more advanced information fusion methodologies and architectures.

In the case of PINS, the MEMS sensors have some limitations and low accuracy, which does not happen on more expensive sensors like the ones used on aviation and military applications. To reduce the sensors complexity and thereby its cost, the information from a set of simple and low-cost sensors can be combined. This leads to the creation of a less expensive system, which captures accurate and reliable information about the pedestrian movements. Moreover, this fusion turns the system more fault tolerant.

This goal is addressed throughout the document, where the system architecture is presented in Section 3. In Section 4 are presented the three implemented algorithms to perform the terrain characterization. One is based on the DTW (Dynamic Time Warping) algorithm, the other on SVM (Support Vector Machines) and the third one is based on a neural network. In Section 5 we present and discuss the obtained results for each implemented method and IMU, or combination of IMUs data. Finally, in Section 6 are discussed the conclusions and the future work.

2. Background

A PINS tries to estimate the person location using the equations of motion through the acceleration information. However, a PINS working by itself cannot keep a good location accuracy over long periods of time. This happens because of the sensors drift and people's different ways of walking.

The approaches that will be presented consist on unassisted PINSs that have applied several different techniques to reduce the PINSs typical errors. One approach, to compensate PINS errors, suggested by Jirawimut [10] and, Lee and Mase [11], is to calibrate the system parameters, the step size and magnetometer bias error, using the GPS signal when the user is in outdoor environments.

The gyroscope bias causes the most orientation estimation errors so a good practice is to calibrate the gyroscope before each experiment. These errors happen more frequently when a low-cost IMU is used, which can produce results 3 times worse than a high cost one. As concluded by some authors [12-13] the uncorrected heading drift is proportional to the walking distance but not to the time elapsed.

To mitigate some of the gyroscope errors Jimenez *et al.*, [13] propose a Heuristic Heading Reduction algorithm. However, one of the best approaches to reduce these errors was proposed by Castaneda and Lamy-Perbal [12], which is a ZARU (Zero Angular Rate Update) algorithm. Ladetto *et al*. [14] have tested two prototypes to estimate orientation, one is based on a gyroscope and the other on a magnetometer. Authors concluded that the best approach, to estimate orientation, is to use a combination of those sensors, since each one have their strengths and weaknesses.

A PINS can be composed by several sensors, so it is very important to implement sensor fusion techniques, like the Kalman filter [15]. Many of the studied works refer the Kalman filter as an optimal estimator, in order to reduce the inertial sensors errors. However, the Kalman filter requires a very good modelling of the system, which can be very complex to perform.

Another difficulty encountered when developing a PINS is the stance phase detection. As stated by Beauregard [16], a dynamic threshold detection algorithm and possibly additional sensors, such as a force or proximity switch, can improve PINS stance phase detection. Hamaguchi [17] has introduced wearable electromagnetic sensors and push button switches attached to user's heels. The results demonstrated that this approach can improve the stance detection, so other systems, like the one proposed by Bebek *et al*. [18] also tended to use similar techniques.

Bebek *et al*. [18] have introduced a high-resolution thin flexible ground reaction sensor to the IMU, which measures zero-velocity duration to reset the accumulated integration errors from accelerometers and gyroscopes in location estimation. This tactile sensor can be used to accurately detect periods of zero-velocity to increase effective positioning resolution. Compared to the other systems, it can be concluded that the inclusion of a tactile sensor improves the step detection since it can detect, with more accuracy, when the foot is on the ground or not.

One aspect that, typically, is not considered is the running gait cycle. However, Li and Wang [19] propose a PINS that uses two zero-velocity detectors, one for each type of gait cycle, walking and running. Authors concluded that the accuracy, of the proposed algorithm, for running cases is comparable to walking ones.

The performance of the presented systems cannot be directly compared since each evaluation scenario is different. In an evaluation of a PINS several variables influence the final results, as is the case of the different pedestrians, the sensors quality, the total distance walked, the type of curves and the environment where the test was performed, like the amount of magnetic disturbances, type of floor (*i.e*. flat or wavy), among others. A variable that has a considerable influence in the PINS results is the step cadence, where the higher errors exist when the user is moving slowly.

Despite all the techniques that are already being implemented errors in PINS are still considerable. It is believed that techniques like information fusion and learning algorithms should be applied to improve the systems estimations. For example, more information sources collected from the human body can be used to improve the system's accuracy because one sensor advantage can suppress another sensor disadvantage. Also, techniques that learn the human gait characteristics in several environments can be used to correct, in real-time, the step distance estimation and the user orientation.

Information fusion combined with artificial intelligence techniques are being used in different INS areas of research to assist in displacement estimation. In robotics, Faceli *et al*. [20] use these techniques to improve the accuracy of distance measurements between a robot and the objects present in the environment by 7%. These techniques are also used in autonomous driving vehicles. Stanley [21] software relied on machine learning and probabilistic reasoning techniques. Its IMU combined with artificial intelligence techniques were able to maintain accurate pose of the vehicle during GPS outages of up to 2 minutes.

In land vehicle applications, Caron *et al*. [22] and Noureldin *et al*. [23] propose machine learning techniques like neural networks, which introduce context variables and errors modelling for each sensor. Authors conclude that with an adequate modelling an accuracy improvement of 20% can be achieved. Recently, Noureldin *et al*. [24] have improved the previous results by considering past position and velocity errors. Bhatt *et al*. [25] propose a hybrid data fusion methodology using Dempster-Shafer theory augmented by a trained Support Vector Machine, which corrects the INS errors. The proposed methodology has shown an accuracy improvement of 20%.

Since these experiences presented good results in the respective area, we wanted to explore similar techniques but applied to PINS. To do this, we make a characterization about the step performed by a pedestrian. This characterization is done using machine learning algorithms. Thus, this work presents a set of experiments that we have performed in order to identify, which learning algorithm achieves the best results.

Another important feature that must be considered is the system wearability. Due to the current developments on the smartphones performance and characteristics, it is likely that in a near future smartphones will handle strapdown calculations in real-time. This is a good opportunity to make the PINS lighter and more integrated with the human clothes.

3. System Architecture

The proposed system is composed by two low-cost IMU, developed by the authors [7], and an “Integration Software”. The “Integration Software” starts by filtering the signals obtained from the sensors and then some features are extracted from the signals, which are used to detect a step and thereby to characterize it according to some previously learned data. Finally, the displacement is estimated based on the collected information. This architecture is represented in Figure 1.

The foot IMU (Figure 2a), placed on the foot, and the waist IMU (Figure 2b), placed on the abdominal area, are composed by a STMicroelectronics L3G4200D gyroscope, an Analog Devices ADXL345 accelerometer and a Honeywell HMC5883L magnetometer.

The foot IMU is also composed by two Tekscan FlexiForcer A201 force sensors, which were included since their information can be used to improve the detection of the moment when the user touches his feet on the ground, as well as, the correspondent contact force. The force sensor combined with an accelerometer improve the accuracy of the step length estimation [8]. One force sensor was placed on the front part of the foot and the other on the heel, as shown in Figure 2a.

Typically in PINS, after a detecting a step the displacement is estimated. However, in our proposal after detecting the step with the algorithm explained in [8] and in [7] a step characterization is made. This characterization is important to eliminate some of the erroneous measurements that are given by the inertial sensors when integrated. This is a very important phase, because it is here that the learning algorithms are applied in order to correct some of the errors provided by the inertial sensors.

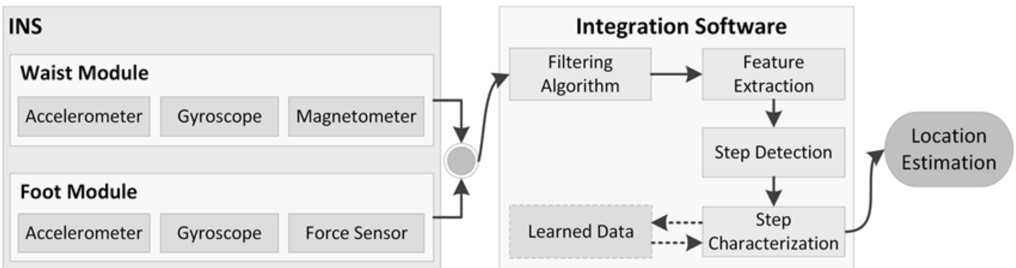
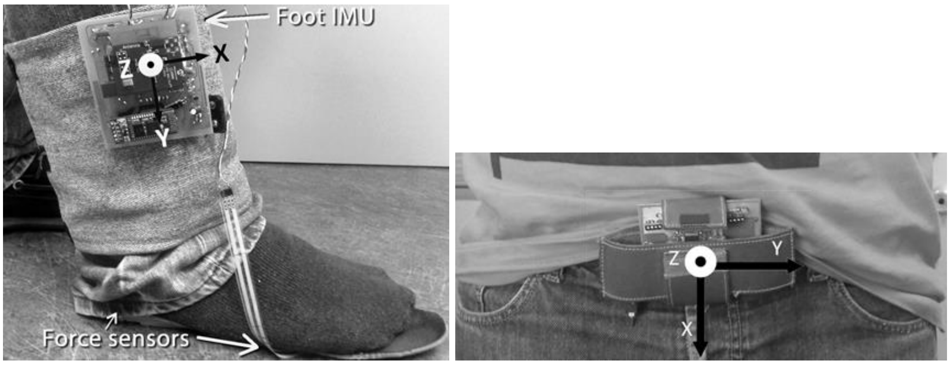


Figure 1. Architecture of the Proposed System



(a) (b)

Figure 2. System IMUs with the Corresponding Axis: a) Foot IMU; b) Waist IMU

Although the accelerometer signal can be integrated in order to estimate the pedestrian displacement, it produces too many errors. However, this signal contains the information needed to be used to classify a step. Even if sometimes this pattern cannot be used to correctly classify a step, it can be surpassed by using several sources of data combined with learning algorithms. Since the probability that more than one source of data give an erroneous signal pattern at the same step is reduced. Thus, the fusion between all the sensors information can improve the number of correct classifications.

A proper model of a step leads to a more correct displacement estimation, since some errors are suppressed in this phase. The proposed system starts the characterization of the step by estimate if the step was performed in a flat terrain, or ascending or descending stairs (*i.e*. step terrain characterization). Then it verifies if it was a forward or a backward one (*i.e*. step direction characterization). This characterization is very important to correctly estimate the pedestrian displacement, since they have opposite directions. The third classification is regarding the step length (*i.e*. step length characterization). This characterization fits into one of three categories: short, normal or long. With this classification we limit the displacement estimation according to the bounds of each category.

These characterizations are performed by combining the data of several sources of information that the system collects from the human body movements. In this work are only presented the results for the step terrain characterization, since similar results were obtained for the other two characterizations.

4. Step Terrain Characterization

To perform the characterization about the type of terrain where a step was given, several algorithms/techniques were implemented and evaluated in order to identify which one provides the most accurate results. Three algorithms were implemented to perform this characterization based on: (i) DTW method (Section 4.1), (ii) SVM (Section 4.2), (iii) and Neural Networks (Section 4.3).

The evaluation of these algorithms will be presented in Section 4.4. The data was first collected and then post processed using Matlab to obtain the results, meaning that the same dataset was used to test each algorithm. These simulations were performed on a low performance computer, in order to have similar results as nowadays high-end mobile device, a Pentium 4 2.8Ghz with 1GB of RAM memory.

To evaluate the advantages of having two sources of information in different parts of the human body (*i.e*. waist and foot) the results are presented for each IMU without fusing their information, and with their information fused, which are represented with the name of the approach combined with the word "Fusion" (*i.e*. DTW Fusion, SVM Fusion and Neural Network Fusion).

Some treatment of the obtained signals is performed before applying the implemented algorithms. Because, giving to a classifier a complete signal can be very heavy and confusing to the machine learning algorithm identify the patterns of the signal and therefore estimate the correct label for that pattern. Usually, features are extracted from the signal to increase the overall performance of the learning system. Meaning that, it generally reduces the dimensionality of a problem domain for the purposes of improving the performance of machine learning algorithms, and to decrease the computational load.

Thus, each learning algorithm will use the raw signals, which are first pre-processed to remove some of the noise, to extract some features from the signals, then classify it and finally will reasoning about the obtained data. This process comprises several stages: data acquisition, signal pre-processing, feature extraction and selection, training and classification.

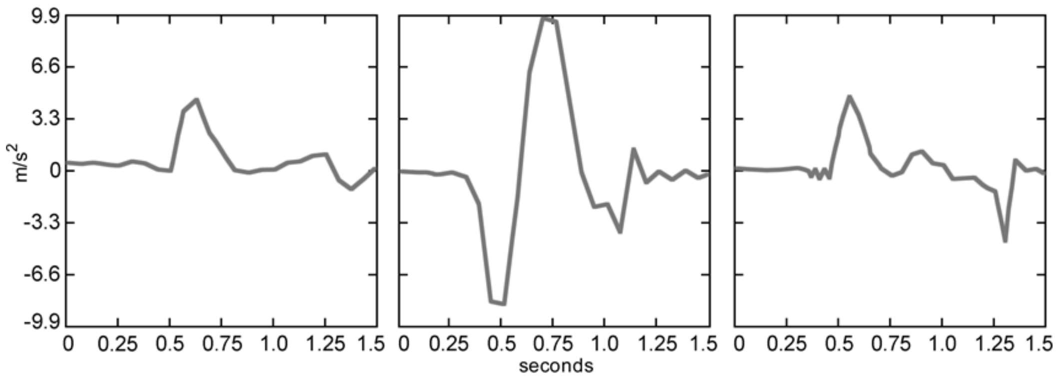
The three implemented algorithms were based on supervised learning, which learns to estimate an output based on a given input. This type of learning needs a lot of experiments in order to have a proper understanding of the problem. The output of these algorithms is a class label. The walking characteristics are learned from a set of exercises previously elaborated by the pedestrian.

The terrain characterization has three possible classes: (i) in a normal (flat) terrain; (ii) in ascending; (iii) or descending stairs. To perform this characterization it was used the data from three sensors: (i) foot accelerometer (*y-axis*); (ii) foot gyroscope (*z-axis*); (iii) and waist accelerometer (*x-axis*). In Figure 3, Figure 4 and Figure 6 are represented an example of the signals that are obtained from these sensors for each class.

The *y-axis* of the foot accelerometer gives a good indication about the foot elevation, which is essential to distinguish between ascending or descending stairs, since the forces are the opposite. However, from the several tests performed it was noticed that the main distinction that can be made using this sensor data is between ascending stairs and the other types of terrain. Visualizing Figure 3b it can be seen that on ascending stairs terrain the acceleration achieves higher values than in the other two cases. This happen because when ascending a stair the foot has to perform a higher elevation than in the other two cases. Regarding the other two types of terrain, descending stairs and normal, the data obtained from this sensor is very similar. The main difference is at the end of the step that, in the case of descending stairs, a higher acceleration is sensed since the foot touches the ground with a higher force than in the normal terrain type.

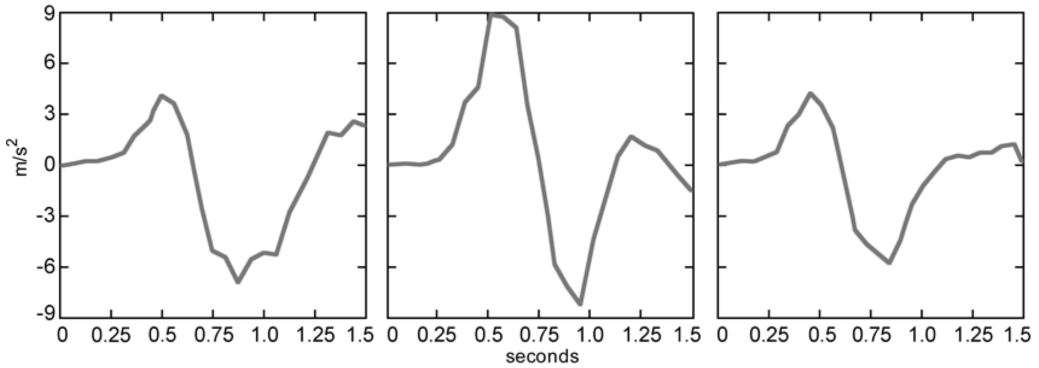
The *z-axis* of the foot gyroscope provides information about the foot rotation in each type of terrain. Comparing the different signals presented in Figure 5, the foot rotation is much more noticeable in the ascending and descending stairs terrains. When ascending stairs, first exists an upward rotation peak and then a downward rotation peak, and it is the opposite when descending stairs. The data from this sensor is very important to make the distinction between these two types of terrain. Regarding the normal terrain, the pattern is similar to the descending stairs. However, the sensed rotation is much softer. Nonetheless this sensor provides a good accuracy on making the distinction between the three types of terrain.

Finally, the *x-axis* of the waist accelerometer provides similar data as the foot accelerometer. In ascending stairs a higher acceleration is sensed, in both positive and negative scales. When descending stairs this acceleration is much lower than in the other two types of terrain.



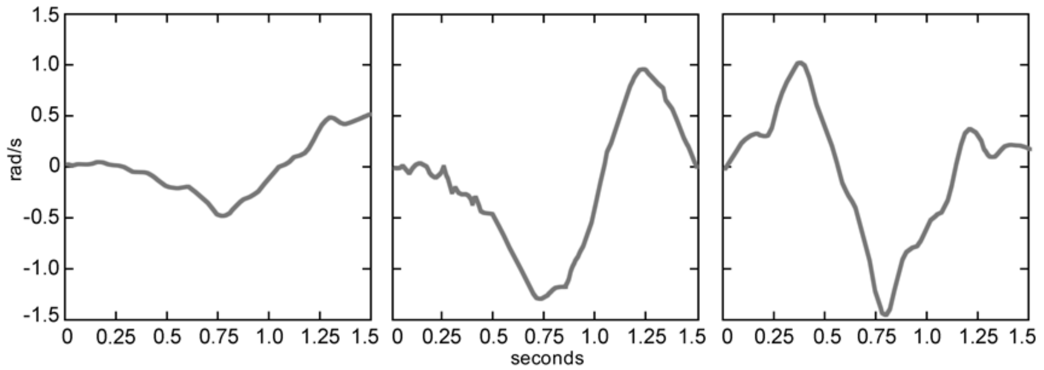
(a) (b) (c)

Figure 3. Foot Accelerometer (y-axis) Data for Each Step Terrain Characterization: a) Acceleration Signal Pattern in a Flat Surface; b) Acceleration Signal Pattern when Ascending Stairs; c) Acceleration Signal Pattern when Descending Stairs



(a) (b) (c)

Figure 4. Waist Accelerometer (x-axis) Data for Each Step Terrain Characterization: a) Acceleration Signal Pattern in a Flat Surface; b) Acceleration Signal Pattern when Ascending Stairs; c) Acceleration Signal Pattern when Descending Stairs



(a) (b) (c)

Figure 5. Foot Gyroscope (z-axis) Data for Each Step Terrain Characterization: a) Gyroscope Signal Pattern in a Flat Surface; b) Gyroscope Signal Pattern when Ascending Stairs; c) Gyroscope Signal Pattern when Descending Stairs

The acceleration sensed in the normal terrain is within the other two. It provides similar data to distinguish between a flat surface and descending stairs. However, when ascending stairs it provides distinguishable data.

Considering the data provided from these signals, it can be established that, combining their data, they are suitable to be used to differentiate each possible characterization terrain. Since the strengths of each signal can be combined to achieve a final consensus.

4.1. DTW

DTW is a time series alignment algorithm [26] that was largely employed in the early speech recognizers. This technique was used to accommodate differences in timing between sample words and templates. Nowadays it is applied to many other fields like bioinformatics, econometrics, robotics, manufacturing, handwriting recognition, data mining, information retrieval, among others to automatically cope with time deformations and different speeds associated with time-dependent data.

This algorithm aims to find the optimal alignment between two sequences of data (*e.g.* time series). After this alignment it calculates the similarity independently of non-linear variations that can exist in the time dimension. It gives intuitive distance measurements between time series by ignoring both global and local shifts in the time dimension, which enables the determination of a degree of similarity between time series.

The optimal warp path is the one that has the minimum distance. The warp path distance is a measure of the difference between the two time series after they have been warped together. It is measured by the sum of the distances between each pair of points connected by the vertical lines. A lower DTW distance denotes a higher similarity. Thus, two time series that are identical, except for localized stretching of the time axis, will have a warp path distance of zero.

Despite the effectiveness of the DTW algorithm, its main problem is that it has a quadratic time and space complexity, $O(n^2)$ that limits its use to small time series datasets.

This implementation works as follows, when a step is detected, the foot accelerometer and gyroscope, and the waist accelerometer signals, are compared, using the DTW algorithm, to a dataset of signals previously obtained for that person.

The dataset, for each sensor, was composed by the data of 108 steps. The dataset can be decomposed into three subsets (one per each terrain type), which were composed by 36 signals each. Since the sensors have an identical pattern through time, this amount of data proved to be sufficient to achieve good results. From the performed tests, less data gives worst results, and more data does not affect significantly the accuracy of this algorithm.

When a step is detected it is calculated the distance between the signals of the detected step with each signal of each subset of signals for a specific type of terrain. The subset that has the lowest mean distance is the one that is closer to the detected step. Thus, the class that the subset represents is returned.

This approach is similar to learning algorithms, since it gives a result based on past experiences. However, this approach is slower and does not generalize as well as the learning algorithms.

4.2. SVM

The SVM algorithm has achieved the best results using as input a set of features retrieved from each sensor signal. From the foot accelerometer are used 6 features: (i) minimum acceleration value; (ii) maximum acceleration value; (iii) difference between the instant moments on which each of the acceleration, minimum and maximum, peak values occur; (iv) difference between the maximum and minimum acceleration peak values; (v) sum of all the negative acceleration measurements; (vi) and the sum of all the positive acceleration measurements.

From the foot gyroscope are used 5 features: (i) minimum rotation value; (ii) maximum rotation value; (iii) difference between the instant moments on which each of the gyroscope, minimum and maximum, peak values occur; (iv) sum of the positive rotations; (v) and sum of the negative rotations.

From the waist accelerometer are used 6 features: (i) maximum acceleration value; (ii) instant moment where the minimum acceleration measurement occurs; (iii) instant moment where the maximum acceleration measurement occurs; (iv) difference between the instant moments on which each of the accelerometer, minimum and maximum, peak values occur; (v) sum of all the negative acceleration measurements; (vi) and the sum of all the positive acceleration measurements.

It gives a total of 17 features that are fed into the SVM algorithm. These features are important since they provide a good indication about the signal pattern. The design of the implemented SVM approach can be seen in Figure 6.

Since in this characterization there are three possible classes (*i.e*. normal, ascending or descending stairs), and the SVM models can only classify two at each time, three SVM models (SVM Model 1, SVM Model 2 and SVM Model 3) were created. From the realized tests it was verified that the best results were achieved using on each model a "polynomial" kernel, configured as a 3th order polynomial.

The models were trained with the same data, but with different class labels vectors. In this case there are three vectors. The first vector, which is used by the SVM Model 1, indicates that the ascending stairs steps belongs to the positive class and the others to the negative.

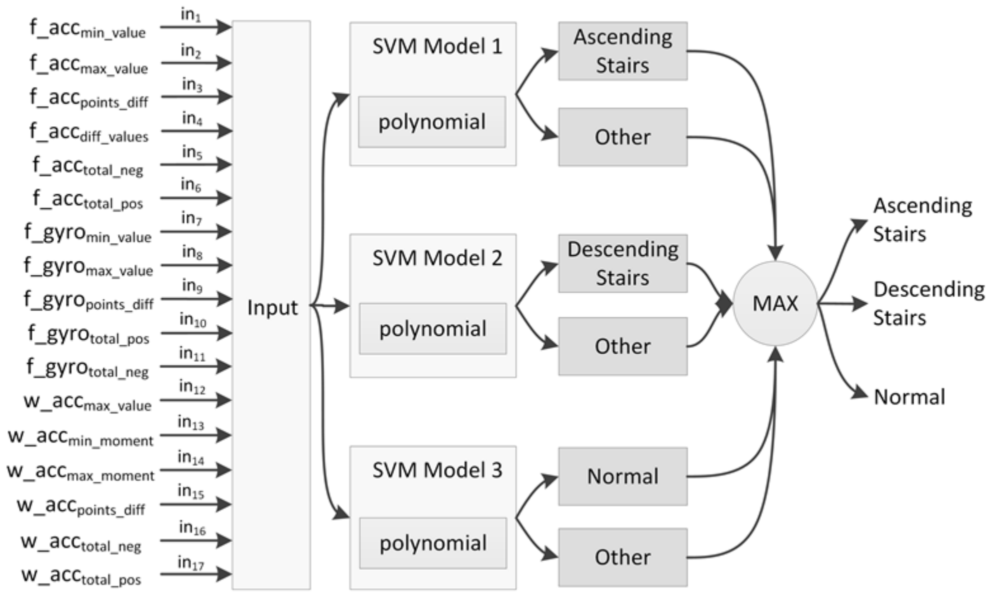


Figure 6. SVM Architecture for Step Terrain Characterization

The second vector, which is used by the SVM Model 2, indicates that the descending stairs steps are the positive entries and the other the negatives. The third vector, which is used by the SVM Model 3, indicates that the normal terrain steps are the positive classifications and the others the negative.

The score of the new observations are then estimated using each classifier. This will create a vector with three scores, one per each classifier. The index of the element with the highest score is the index of the class to which the new observation most likely belong. For example, if the first index has the highest value, then the step is classified as ascending stairs. Thus each new observation is associated with the classifier that gives to it the maximum score.

After the learning phase, a 10-fold cross validation to the model was performed. The SVM Model 1 presented no error, the SVM Model 2 presented an error of 0.8% and the SVM Model 3 presented an error of 2.6%.

4.3. Neural Network

For the neural network algorithm the best results were obtained using 72 inputs (24 inputs per each sensor). Where each sensor signal is divided into 6 equal parts, and for each one of these parts the maximum, minimum and mean values were obtained, as well as, the slope. The slope was calculated based on the first and the last measurement of each part. This data gives a total of 24 inputs per each sensor that are fed into the learning algorithm.

The same features that were used as input of the SVM (Section 6.1.1.1) were tested as input of the implemented neural network. However, from the several tests performed, these features (72 inputs) were the ones that gave the best results on classifying the type of terrain.

It was decided to divide the signal in 6 parts, because, during a step, each sensor signal is typically composed by 30 measurements. Thus, in order to have an average of 5 measurements per iteration the signal was divided into 6 equal parts. More parts will divide the signal too much, and less parts will pass insufficient information to the learning algorithm. Thus, the 6 was the number of parts that best represent each one of the signals.

In Figure 7 is represented the design of the implemented neural network that classifies the type of terrain. The neural network receives as input (j) the 72 features previously presented. This input is passed to the Hidden Layer, which is composed by 144 neurons. Then, the Output Layer returns the final result about the type of terrain where the step was given.

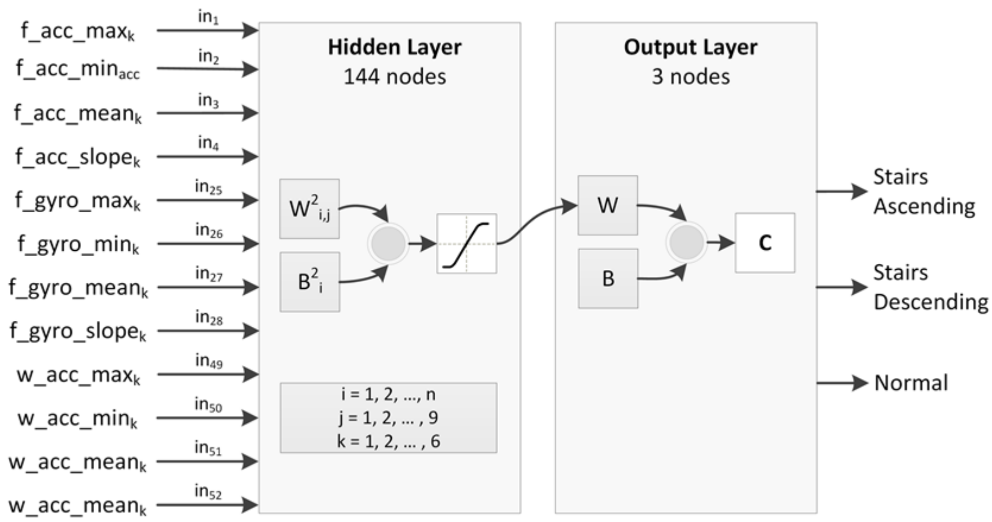


Figure 7. Neural Network Architecture for Step Terrain Characterization

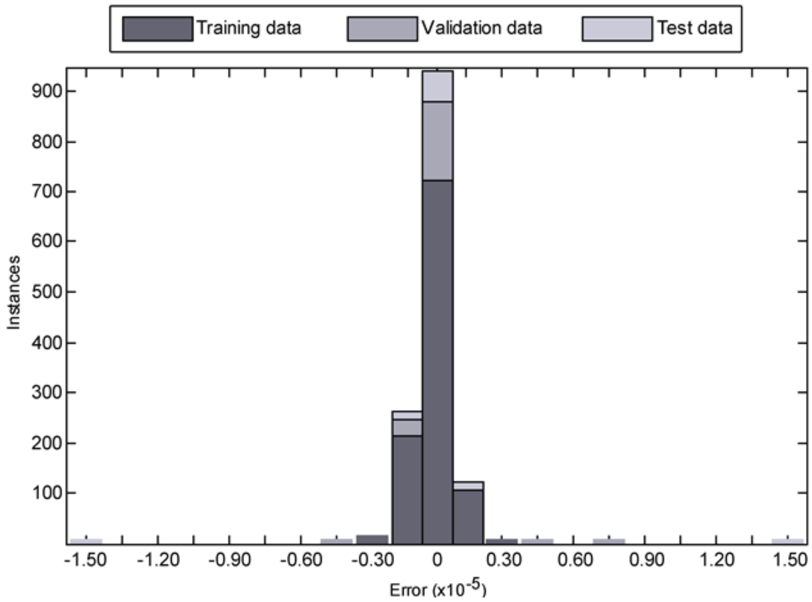


Figure 8. Neural Network Training Error Histogram for Step Terrain Characterization

The neural network parameters namely, the number of neurons in the hidden layer, the learning rate and the number of iterations, were tuned by trial and error. The learning rate was defined as 0.01 and the number of iterations as 36.

The mean squared error of the best validation performance was 7.97×10^{-7} with a gradient of 9.80×10^{-7} at epoch 36. The error histogram can be seen in Figure 8. From this figure it can be concluded that the error given by the neural network is very low, where more than 98% of the results are very close to zero error. The highest error for an instance, during the network training, was of 1.50×10^{-5}.

5. Evaluation

The three implemented algorithms were evaluated using a dataset of 800 steps performed by two pedestrians (400 steps for each pedestrian).

The test scenario is the path represented in Figure 9, which involves a complex path with a set of straight walks and a set of stairs. The set of stairs was ascended two times and descend one time. Meaning that, the pedestrian ascended the stairs, then descend it and finally ascended it again.

A total of 200 steps, each time, were performed in this scenario which gives a total walking distance of 70 meters. Two runs in this scenario, for each pedestrian, were performed. The results obtained for this scenario can be seen in Table 27. This table presents for each algorithm, the categorization accuracy (in percentage) and the execution time (in milliseconds). For all the algorithms are presented the results obtained in separate for each IMU, and for the combination of the data of both IMU. This comparison shows clearly which IMU has better accuracy for each characterization type.

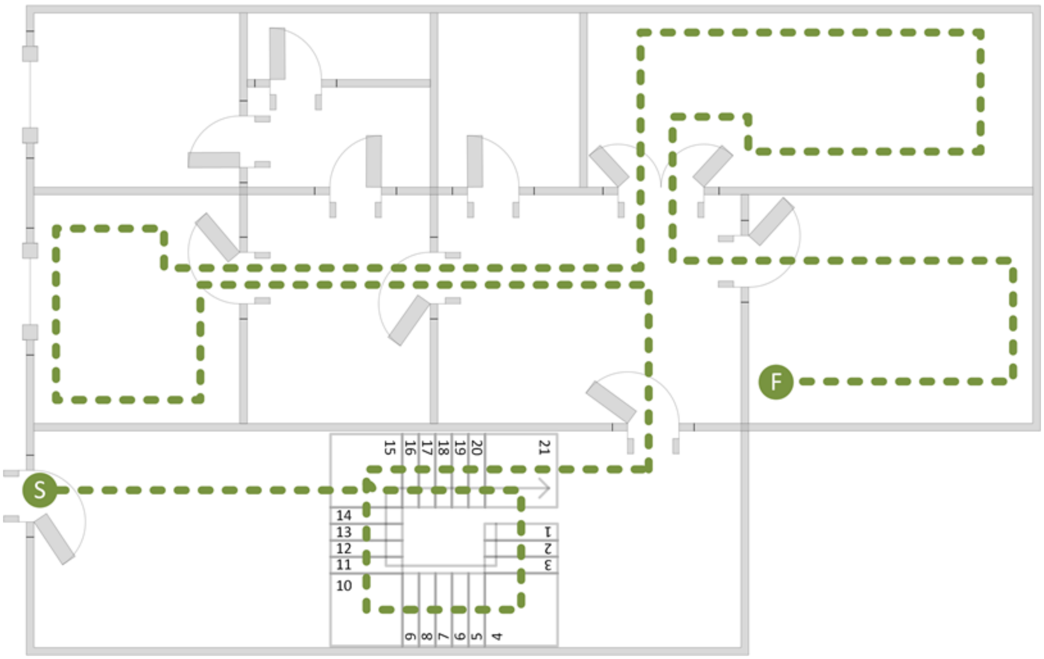


Figure 9. Evaluation Scenario

Table 1. Accuracy Results for the Developed Algorithms that Characterize the Step Terrain

Method	Ascending		Descending		Normal		Execution Time
	Waist IMU	Foot IMU	Waist IMU	Foot IMU	Waist IMU	Foot IMU	
DTW	59%	93%	98%	100%	69%	87%	400 ms
SVM	97.5%	99.4%	94.2%	99.4%	85.1%	94.9%	1 ms
Neural Network	98.3%	100%	94.1%	100%	87.2%	94.9%	1 ms
DTW Fusion	95%		99%		89%		600 ms
SVM Fusion	99.4%		99.5%		96.2%		2 ms
Neural Network Fusion	100%		100%		98.7%		2 ms

Considering the obtained results it can be concluded that the ascending stairs class is the easiest to classify. All the algorithms, except the DTW approach, presented the best results when classifying this class. The normal terrain class is sometimes confused with the descending stairs class, so it is with this misclassification that most errors occur.

Regarding the IMUs, the foot IMU gives more accurate data, since the foot is closer to the ground. The waist IMU can give a good indication about the vertical movement of the body. However, it obtains similar data when descending stairs and in normal terrain. Thus, it presents worst results in these classifications.

The DTW approach revealed to have worse results when compared to the others. This happens because the signals are pretty much similar, varying only the intensity of the peaks. Also, it is the one that takes longer to run.

Analyzing the obtained results for each algorithm, when considering the fusion of both IMU, the learning algorithms presented the best results. The best was the Neural Network, achieving a mean accuracy of 99.4% and having 100% of accuracy on predicting the ascending and descending stairs classes.

From the obtained results, it can be concluded that through the sensors complementarity the type of terrain was categorized with higher accuracy. Also, it can be concluded that the learning of the gait parameters enables a better characterization of a step. From our tests it was identified that a learned dataset 5 times smaller, than the used one, is sufficient to achieve similar results. Making the learning procedure simpler and faster to a pedestrian perform before using the proposed system.

6. Conclusions

Develop a PINS to be used by pedestrians in their daily life is a huge challenge. Many approaches already have been proposed, but must of them rely on a structured environment that usually is infeasible to implement and the others do not provide the necessary accuracy.

To suppress some of these limitations we propose a PINS based on fusion and learning techniques. The proposed system characterizes the step according to the activity that the pedestrian is performing. After the type of terrain this characterization verifies the step direction, which is very important to correctly estimate the pedestrian displacement, since they are opposite directions. Then it is verified the step length, which is important to limit the displacement estimation according to the bounds of each category.

Combining the two sources of data, waist IMU and foot IMU, the quality of the data is improved, since the probability that two sources of data give erroneous measurements patterns at the same time is much reduced. The fusion between all the sensors information improves the number of accurate classifications. Thus, this integration leads to a better characterization of the step.

The use of the step characterization, through the use of more than one IMU and the neural network algorithm led to an improvement, compared to the previous results [7], in displacement estimation of 34%. In the same scenario the error has decreased from 7.3% to 4.8%.

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