Step Count and Classification using Sensor Information Fusion

Ricardo Anacleto[1*], Lino Figueiredo[1], Ana Almeida[1], Paulo Novais[2], and António Meireles[1]

[1] GECAD - Knowledge Engineering and Decision Support Research Center, School of Engineering - Polytechnic of Porto, Porto, Portugal
{rmsao,lbf,amn,ajmme}@isep.ipp.pt

[2] CCTC - Computer Science and Technology Center, at University of Minho, Braga, Portugal
pjon@di.uminho.pt

Abstract. In order to suppress the GNSS (Global Navigation Satellite System) limitation to track persons in indoor or in dense environments, a pedestrian inertial navigation system can be used. However, this type of systems have huge location estimation errors due to the Pedestrian Dead Reckoning (PDR) characteristics and the use of low-cost inertial sensors. To suppress some of these errors we propose a system that uses several sensors spread in person's body combined with information fusion techniques. Information fusion techniques provide lighter algorithms implementations, to count and classify the type of step, to run in mobile devices. Thus, improving pedestrian inertial navigation systems accuracy.

Keywords: Pedestrian Inertial Navigation System, Step Count, Information Fusion, Dynamic Time Warping

1 Introduction

A system that is capable to locate an individual can be explored to improve life quality since emergency teams (fire-fighters, military forces [5] and medics) can respond more precisely if the team members location is known, tourists can have better recommendations [8], the elderly can be better monitored [9] and parents can be more relaxed with their children in shopping malls [3].

Usually these applications retrieve pedestrian's location by using a GNSS (Global Navigation Satellite System). Unfortunately, GNSS signals aren't available inside buildings or in dense environments. Consequently location-aware applications sometimes cannot know the user location.

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There are already some proposed systems that retrieve location in indoor environments. However, most of these solutions require a structured environment [6]. Therefore, these systems could be a possible solution for indoor environments, but in a dense forest or urban canyons they are difficult to implement.

To suppress structured environment limitations, a Pedestrian Inertial Navigation Systems (PINS) can be used. Typically, a PINS is based on an algorithm that involves three phases: step detection, step length estimation and heading estimation. A PINS uses accelerometers, gyroscopes, among other sensors, to continuously calculate via dead reckoning the position and orientation of a pedestrian. These sensors are based on MEMS (Microelectromechanical systems), which are tiny and lightweight sensors making them ideal to be integrated into the person's body or clothes. Unfortunately, large deviations of inertial sensors can affect these systems performance, so the PINS big challenge is to correct the sensors deviations.

In the research team previous works, the step detection was improved by using an algorithm that combines an accelerometer and force sensors placed on the pedestrians foot [2]. Then this led to better results [1] 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.

We have found that a PINS solution only based on one IMU (Inertial Measurement Unit), composed by an accelerometer and a gyroscope, is not accurate enough. Thus we believe that using several IMU in the person's body, combined with a information fusion strategy, will improve the accuracy of PINS.

This goal is addressed throughout the document, where the system architecture is presented in Section 2 and the developed algorithms, that detect pedestrian steps and classify them, are presented in Section 3. In Section 4 the experimental results are given and, finally, in Section 5 are discussed the conclusions and the future work.

2 System Architecture

The proposed system is composed by two low-cost IMU, developed by the authors [2], and an "Integration Software" (described in Section 3) that integrates the information from the IMUs to count and classify the pedestrian steps. The system architecture is demonstrated in Figure 1.

When referring to a low-cost IMU it implies different things for researchers, since for some a thousand euros IMU is considered low-cost. However, for PINS a low-cost IMU should cost less than €100. This price restriction, implies the use of MEMS sensors that are truly low-cost.

The first IMU (Waist IMU), presented in Figure 2a, is placed on the abdominal area and is composed by a STMicroelectronics L3G4200D gyroscope [12], a Analog Devices ADXL345 accelerometer [4] and a Honeywell HMC5883L magnetometer [7]. The second IMU (Foot IMU) is placed on the foot and is presented in Figure 2b. It is composed by an Analog Devices ADXL345 accelerometer [4], a STMicroelectronics L3G4200D gyroscope [12] and two Tekscan FlexiForce®

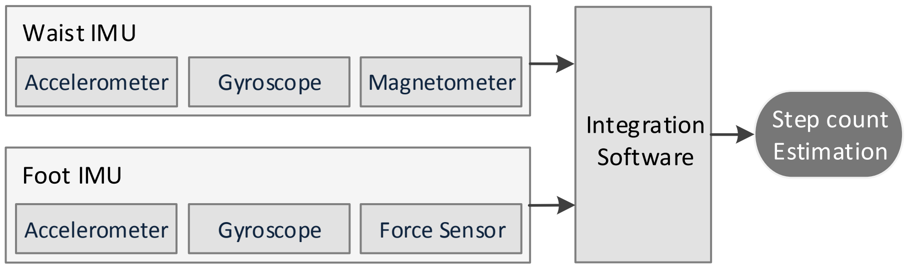


Fig. 1: System Architecture

A201 force sensors [13]. The accelerometer is used to detect and quantify the foot movement, and the gyroscope is valuable to transform the acceleration data from the sensor frame to the navigation frame.

Force sensors were included since they can improve the process of detection of the moment when the user touches his feet on the ground, as well as, the correspondent contact force, which combined with the accelerometer improve the accuracy of the step length estimation. One force sensor was placed in the front part of the foot and the other in the heel, as shown in Figure 2b.

The IMU collects the data with a rate of 100 Hz. However, the mean of the last five readings is made to reduce some of the errors, meaning that the data rate decreases to 20Hz, which is sufficient to include the signal frequencies induced by the walking of a pedestrian.

Next section will present the “Integration Software” which classifies the step.

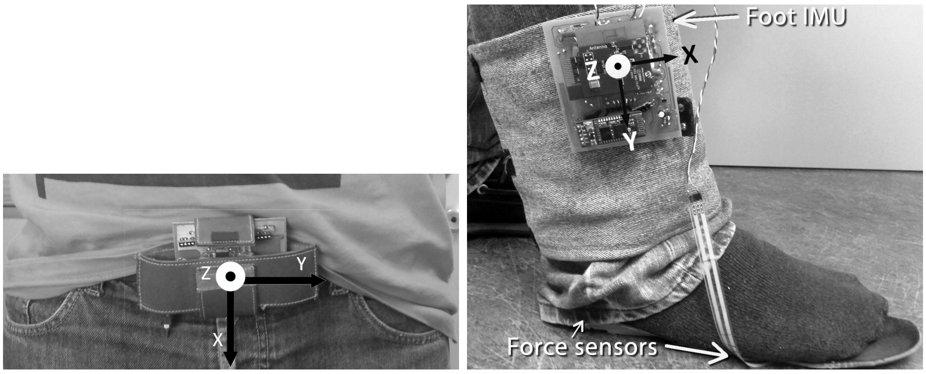
3 Step count and classification algorithms

From previous experiences the step detection and classification using only an accelerometer or an accelerometer and a force sensor, still has some error.

In Figure 3a is represented an acceleration signal obtained from the foot accelerometer, for a backward step. It can also be seen a simulated acceleration signal, which is the one expected when a backward step is given. As can be seen the accelerometer doesn’t capture the accelerations in a perfect form, but it contains the information needed to be used to classify a step.

Although the pattern of the acceleration can be used to classify a step, sometimes the accelerometer produce a signal that doesn’t follow any pattern, which turns to be useless to correctly classify a step. In Figure 3b is represented an acceleration signal, that had occurred in a forward step, that doesn’t follow any pattern. This acceleration signal can’t be used to correctly classify a step.

Using several sources of data can be useful to surpass some of these random readings. The probability of two sources of data give erroneous acceleration patterns at the same step is very reduced. The fusion between all the sensors information can improve the number of correct classifications. However, the integration of more than one IMU can be very difficult to implement.



(a) (b)

Fig. 2: Foot (a) and Waist (b) IMU with the corresponding axis

The objective of this proposal is to detect and classify a step given by a pedestrian, combining several sources of information. After the detection of a step, with the algorithm explained in [1] and in [2], the proposed algorithm classifies the step as forward or backward.

Three algorithms were implemented to classify the direction of a step. The first one is based on some heuristics (Section 3.1). The second is based on a Dynamic Time Warping (DTW) [10] approach (Section 3.2). Both use only the data of one IMU. The third one (Section 3.3) uses a heuristic approach and a weight fusion technique to combine the data from the two IMU, to achieve a consensus about the characterization of the step.

Due to the existence of more than one IMU, an important issue is the data time synchronization. During data collection both IMU sensor data must be synchronized with an accuracy sufficient for this type of application. In our case, when the foot IMU data is received by the waist IMU, a timestamp is assigned to the data.

3.1 Heuristic Method

Typically a PINS detects a step by using the accelerometer data and by analyzing the forward and upward accelerations during the walking path. Typically, the detection is performed by using at least one of these three methods: peak detection, zero crossing detection and flat zone detection. Analyzing the literature can be seen that the peak detection is the most used method. However, peak and zero crossing detection algorithms can miss or over detected some steps because of accelerometer erroneous signal.

This sensor signal also shows distinguishable characteristics for walking characterization.

After smoothing the raw acceleration data and to classify the direction of the step, in both IMU, the Equation 1 was used.

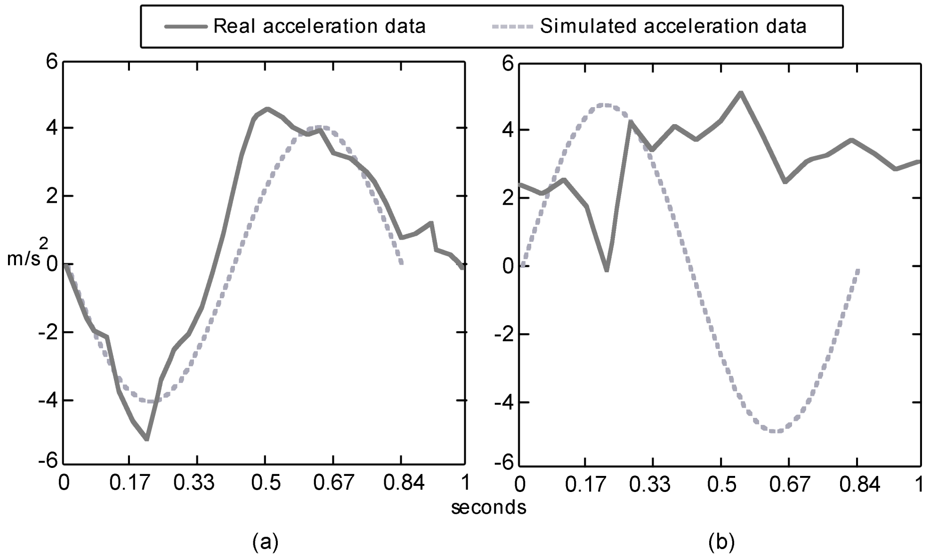


Fig. 3: (a) Acceleration data sensed, by the foot accelerometer, in a backward step; (b) Erroneous acceleration data sensed, by the foot accelerometer, for a forward step

$$\sum_{i=1}^{\frac{n}{2}} acc_i > \sum_{i=\frac{n}{2}}^{n} acc_i \tag{1}$$

where n represents the number of acceleration values detected for the step, acc is the acceleration values sensed on the x axis, in the case of the foot IMU, and on the z axis, in the case of the waist IMU.

This formula sums the first half of the signal and compares it with the sum of the second half. If the first is positive or higher than the second it is a forward step, if not it is a backward step. From our tests the maximum number of acceleration samples for a step was 60, meaning that this algorithm is fast to process.

3.2 Dynamic Time Warping Method

DTW is a well-known technique, in time series analysis, which finds an optimal alignment between two given time series. It is mainly used to measure the similarity between two temporal sequences which may vary in time or speed. The main problem is that the DTW algorithm has a quadratic, $O(n^2)$, time and space complexity that limits its use to only small time series data sets. It gives intuitive distance measurements between time series by ignoring both global and local shifts in the time dimension, which allows to determine the similarity between time series. A lower DTW distance denotes a higher similarity.

Our algorithm works as follows, when a step is detected, by the algorithm described in [2], the foot accelerometer and the waist accelerometer waveforms, are used to be compared to the series previous learned for that person. Then, for a series of previously categorized steps, the algorithm calculates the DTW distance between the detected step and the ones stored, to see which is the category that corresponds to the performed step. The category that as the minimum distance to the stored waveforms, is the one that is chosen.

In our tests a dataset of 24 (12 forward and 12 backward) of previously learned and categorized steps was used. Since the acceleration has an identical pattern through time, this amount of data proved to be sufficient to achieve good results.

3.3 IMUs Information Fusion Method

The two IMUs placed in the person's body allows to combine the information given by them in order to minimize the complexity of the algorithms and maximize the accuracy and the robustness of the navigation solution.

Typically there are three types of fusion: data fusion, feature fusion and decision fusion. In this case the decision fusion was chosen. For each source of data, foot accelerometer and waist accelerometer, it is calculated the probability of the predicted result. This probability is calculated, according to Equation 2, which is based on the fact that a positive acceleration must be followed by a negative acceleration of the same magnitude, and vice-versa.

$$stepprobability = 100 - (abs((max(acc) + min(acc))) \times 20) \tag{2}$$

If the acceleration signal doesn't follow this pattern then a low probability is given to it. For the acceleration example shown in Figure 3a the probability that it is a characterizable step is 100% and for the example shown in Figure 3b the probability is only 20%.

After the calculation of this probability, a weight is given to each one of the data sources. The foot IMU has a weight of 0.6, since it is the most reliable source of data, and the waist IMU has a weight of 0.4.

4 Experimental Results

The developed system and algorithms were evaluated by using a dataset of 200 steps performed by two pedestrians (100 steps for each pedestrian). The data was collected and then post processed using Matlab to obtain the results, meaning that the same dataset was used to test each algorithm.

The test scenario is a straight walk with two 90° turns, in the middle of the path, one to the left and the other to the right. A total of 25 steps (13 forward and 12 backward), each time, were performed in this scenario which gives a total traveled distance of 10 meters and a displacement of 5 meters. Four runs in this scenario, for each pedestrian, were performed.

The obtained results can be seen in Table 1. This table presents for each algorithm, the categorization accuracy (in percentage) for each IMU and the execution time (in milliseconds). The simulations were performed on a low performance computer, a Pentium 4 2.8Ghz with 1GB of RAM memory.

Table 1: Results for the three implemented algorithms

Method	**Forward**		**Backward**		**Execution time**
	Waist IMU	**Foot IMU**	**Waist IMU**	**Foot IMU**	
Heuristics	82.1%	97.4%	74.4%	94.9%	1 ms
DTW	84.6%	100%	79.5%	97.4%	100 ms
IMUs Information Fusion	100%		98%		2 ms

From the obtained results, it can be concluded that the waist IMU produces more errors than the foot IMU. This mainly happens because when the user is moving the foot is a more stable platform than the waist. A lot of unwanted accelerations are sensed by the waist, which leaves to a poor characterization of the step, but there are some features that can be retrieved to help other sources to properly characterize the step.

Regarding the step characterization the backward one is more difficult to classify than the forward one. Mainly because of the errors, presented on Section 2, that can occur in the accelerometer readings.

Comparing the DTW approach with the Heuristic one, it can be seen that the DTW has lower errors. However, it has an execution time 100 times longer than the Heuristic one. In order to maintain a lower execution time and an accuracy similar to the DTW approach, the information of both IMUs was fused. Through the sensors complementarity the step was categorized with similar accuracy but with an execution time 50 times smaller. This is an important help in order to improve the pedestrian displacement estimation. Using IMUs in different locations on pedestrian body, waist and foot, was very important to have these results.

5 Conclusion

Develop an accurate, inexpensive and small PINS to be used by persons, when they are on foot can be a huge challenge. Many approaches already have been proposed, but must of them rely on a structured environment that usually is unfeasible to implement and the other's don't provide the necessary accuracy.

In this work two IMUs were used, one on the foot and the other on the waist, where their data was explored to the maximum in order to provide an acceptable level of performance. Since the detection of stance phase using only accelerometers can introduce several errors on PINS, our proposal uses information fusion techniques to improve step detection and its classification. Through the use of these techniques an average accuracy of 99% was achieved, which is very satisfactory.

In the future we want to use this step classification to improve distance estimation. Also, we want to use different estimation algorithms for each state, forward or backward, because it is more natural for a human to perform a forward step than a backward one. Meaning that the patterns for a forward step are more constant than for a backward step, since it isn't natural to us do that type of movement.

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