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Pedestrian Inertial Navigation System with Terrain Characterization using Information Fusion

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Abstract. Pedestrian inertial navigation systems are an alternative to systems that are based on structured environments. However, due to low-cost inertial sensors and pedestrian dead reckoning inherent characteristics, these systems provide huge location estimation errors. Thus, we propose a system that uses two inertial measurement units spread in person's body, which measurements are used by a neural network to learn the human gait behavior. In this work we demonstrate how this neural network is used to characterize the step according to the type of terrain, which can be flat and ascending or descending stairs. These terrains are the ones that are most encountered inside a building.

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

1 Introduction

Location is an important source of context that can be used to improve mobile applications quality [5]. Typically, this information is obtained using a GNSS (Global Navigation Satellite System). However, GNSS signals are not available inside buildings or in dense environments. Therefore, location cannot be retrieved without the usage of complementary structured environments [7]. However, the implementation of such systems can be complex and expensive.

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 and heading estimation. A PINS uses accelerometers, gyroscopes, among other sensors, to continuously calculate via dead reckoning the position 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 given by inertial sensors can affect performance.

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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 pedestrians foot [2]. This approach lead 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.

Thus, 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. We believe that using several IMU in the person's body, combined with an information fusion strategy, will improve the accuracy of PINS.

Information fusion combined with artificial intelligence techniques are being used in different INS fields to assist in displacement estimation [6]. In land vehicle applications, Caron et al. [4], Noureldin et al. [8] and Bhatt et al. [3] 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.

Since these experiences presented good results in the respective area, we are exploring similar techniques but applied to PINS. Our proposal applies an information fusion from several IMU spread in the person's body, and learning algorithms that classify the type of terrain where a step was given.

With this characterization the step length can be corrected, since some boundaries can be applied for each characterization. Also, the vertical displacement can be better estimated since it will be only considered when the pedestrian is on stairs terrain. Thus, improving the accuracy of the proposed PINS.

This goal is addressed throughout the document, where the system architecture is presented in Section 2. In Section 3 is presented the neural network that characterizes a step according to the type of terrain. In Section 4 are presented the results obtained on comparing the use of only one IMU versus the usage of the two IMU, as input of the neural network. Finally, in Section 5 are discussed the conclusions.

2 System Architecture

The proposed system (Figure 1) is composed by two low-cost IMU, developed by the authors [2], and an "Integration Software". The "Integration Software" filters the sensors signals, then some features are extracted from them, which are used to detect and characterize a step (Section 3).

The first IMU (Waist IMU) is placed on the abdominal area, and the second IMU (Foot IMU) is placed on the foot. Both IMUs are composed with a STMicroelectronics L3G4200D gyroscope and a Analog Devices ADXL345 accelerometer. The waist IMU has also a Honeywell HMC5883L magnetometer, and the foot IMU has two Tekscan FlexiForce® A201 force sensors. One force sensor was placed on the front part of the foot and the other on the heel.

In the "Step Characterization" phase three characterizations are made: (i) terrain, which distinguishes between a normal (flat) terrain, and ascending or descending stairs, and is the characterization that is presented in this work; (ii)

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step direction, which makes the distinction between a forward or a backward step; (iii) step length, that distinguishes between a small, normal and long step. With this characterization through machine learning techniques, the overall performance of the PINS is improved, mainly regarding its accuracy. Finally, the displacement is estimated based on the collected information.

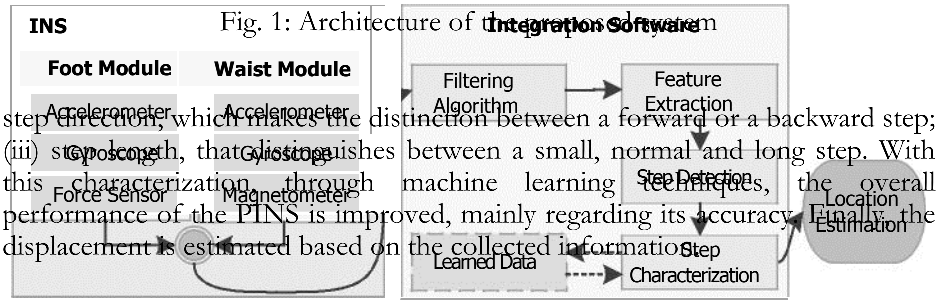

Fig. 1: Architecture of the proposed system

3 Step Terrain Characterization

Inertial sensors present too much erroneous readings, thus one possible solution is to use its signal pattern to classify and distinguish the data captured by the sensors. Having a proper model of a step enables a more accurate displacement estimation, since some errors can be suppressed using this model.

For example, the accelerometer does not capture perfectly the accelerations, thus the integration of the acceleration produces several errors. However, it contains reliable information to classify a step. Although the pattern of the acceleration can be used to classify a step, sometimes the accelerometer produce a signal that does not follow any pattern, which turns to be useless to correctly classify a step. However, these random readings can be surpass by using several sources of data, since the probability that two sources of data give erroneous acceleration patterns at the same step is very reduced. Thus, the fusion between all the sensors information can improve the number of correct classifications.

The characterization presented in this work is about the terrain where a step was given. There are three possibilities, a normal (flat), ascending stairs or descending stairs. The neural network receives as input the foot IMU accelerometer and gyroscope data, and the waist IMU accelerometer data. These sensors are important to perform this characterization, since the *y-axis* of the foot accelerometer gives a good indication about the elevation that the foot performs, which is essential to distinguish between ascending or descending stairs, since the forces are the opposite. The same happens in the pedestrian's waist, thus the *x-axis* accelerometer positioned in that location also provides good accuracy on obtaining that information. The gyroscope (*z-axis*) on the foot provides information about the rotation that the foot performs in each type of terrain.

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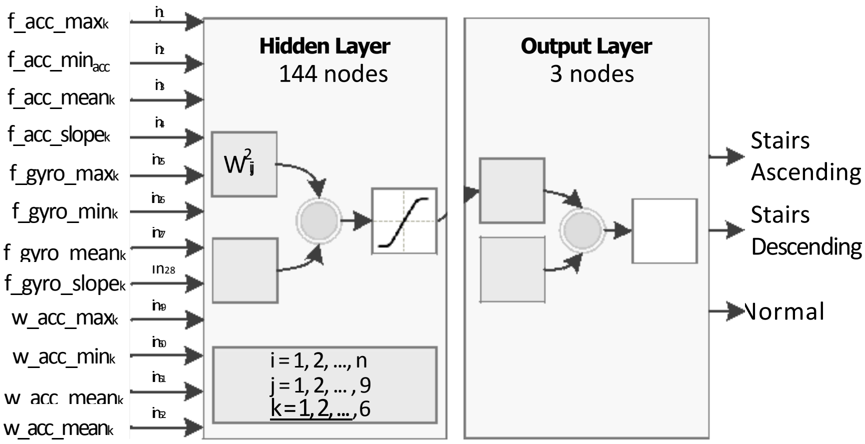

Fig. 2: Neural network architecture for step terrain characterization

Considering the data obtained from these signals it can be established that they are suitable to be used to differentiate each possible characterization terrain.

During a step each sensor signal is typically composed by 30 acceleration measurements. Thus, in order to have an average of 5 measurements per iteration the signal was 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 on the last measurement of each part. Thus, the neural network as 72 inputs (24 inputs per each sensor).

This division was made because giving to a classifier a complete signal can be very heavy and confusing to the algorithm to identify the patterns of the signal and therefore estimate the correct label for that pattern. Thus, we reduce the dimensionality of the problem domain for the purposes of improving the performance of the algorithms and to decrease the computational load. From the several tests performed, these features were the most important in order to correctly classify the possible terrain where the step was given.

In Figure 2 is represented the implemented neural network, which receives as input (j) the 72 features previously presented, which are then passed to the *Hidden Layer*, which is composed by 144 neurons. Then, the *Output Layer* returns the final result about the step terrain.

The neural network was trained with a total of 970 samples, 358 samples of ascending stairs steps, 358 samples of descending stairs steps and 254 samples of normal terrain steps. To validate the algorithm a total of 170 samples were used (62 ascending, 62 descending and 46 normal) and to test the algorithm a total of 540 samples were used (180 ascending, 260 descending and 100 normal). A 10-fold cross-validation using these datasets was also performed. The learning rate was defined as 0.01 and the number of iterations as 36.

The mean squared error was 7.97×10^{-7}. Analyzing the error histogram it was concluded that the error given by the neural network is very low, where

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more than 98% of the results are very close to zero error. The biggest error for an instance, during the network training, was of 1.50×10^{-5}.

4 Evaluation

The neural network was evaluated using a dataset of 800 steps performed by two pedestrians. One is a male with a height of 1.90m and the other is a female with a height of 1.65m. The test scenario involves a path with a set of straight walks and a set of stairs, which the pedestrians have ascended and descended two times. A total of 200 steps, each time, were performed in this scenario, which gives a traveled distance of 70m.

To verify the advantages of using multiple IMU in the pedestrian's body, the implemented neural network was tested against a similar one, but that receives as input, one IMU sensors per test. Thus, we have three different results: (i) for the foot IMU data; (ii) for the waist IMU data; (iii) for both IMU data. The obtained categorization accuracy results can be seen in Table 1.

Table 1: Accuracy results obtained for the step terrain characterization

Method	Ascending		Descending		Normal	
	Waist IMU	Foot IMU	Waist IMU	Foot IMU	Waist IMU	Foot IMU
Neural Network	98.3%	100%	94.1%	100%	87.2%	94.9%
Neural Network Fusion	100%		100%		98.7%	

Analyzing the results it can be concluded that the ascending stairs class is the easiest to classify. The normal terrain class is sometimes confused with the descending stairs class, it is with this misclassification that most errors occur. By combining two sources of data the quality of the data is improved.

Regarding the IMUs, the best results were achieved with the foot IMU, since it is closer to the ground. The waist 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 "Neural Network Fusion" achieved a mean accuracy of 99.4%, with a 100% accuracy when predicting the ascending and descending stairs classes.

5 Conclusion

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

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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.

The use of the step characterization, through the use of more than one IMU and the neural network algorithm, lead to an improvement, compared to the previous results [1], in displacement estimation of 34%. In the same scenario the error has decreased from 7.3% to 4.8%.

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