Improving Inertial Navigation Systems with Pedestrian Locomotion Classifiers

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Keywords: Machine Learning, Inertial Navigation System, Sensors.

Abstract: Researches on inertial navigation systems (INS) have formulated complex step detection algorithms and stride length estimations. But for current systems to work, INSs have to correctly identify negative pedestrian locomotion. Negative pedestrian locomotion are movements that a user can naturally make without any real position displacement, but has sensor signals that might be misidentified as steps. As the INS's modules have a cascading nature, it is important that these false movements are identified beforehand. This research aims to provide a solution by studying patterns exhibited by positive and negative pedestrian locomotion when sensors are placed on a user's front pocket. A model was then built to classify negative from positive pedestrian locomotion, and to improve the INS's accuracy overall.

1 INTRODUCTION

Indoor navigation systems determine where a device has traversed inside a building. These navigation systems can be employed in applications to help users find a specific location in closed places like conference centers and office buildings. Unlike outdoor navigation systems like the Global Positioning System (GPS), indoor navigation systems cannot use satellite signals as heavy attenuation takes place when the signals make their way through physical obstacles.

To solve this, researchers have experimented with Wi-fi signals like (Bahl and Padmanabhan, 2000a), (Bahl and Padmanabhan, 2000b), (Battiti, 2005), (Youssef et al., 2003), and (Youssef and Agrawala, 2004); vision (Karlsson et al., 2005); ultra-wide bands (Teuber and Eissfeller, 2006); cellular-based signals (Otsason et al, 2005); magnetometers (Chung et al., 2011); and combinations of these (Brunato and Battiti, 2005). All of these researches are dependent on environment variables such as Wi-fi routers and markers, and some require data collection prior to system use. This would mean that a significant change in the environment or the variables would affect the performance of these navigation systems.

INSs, on the other hand, uses data from inertial sensors such as gyroscopes and accelerometers to determine the path a device has travelled. Smart phones currently already have these sensors as micro-electrical-mechanical systems (MEMS) devices, making it possible for INSs to be applied in smart devices and possible for ubiquitous use. Compared to other navigational systems, INSs are independent of its environment, requiring less cost that otherwise would have incurred with the need of access points. This also implies less environment set-up as access points do not need to be installed for the navigation system to operate. Considering that it is a cheaper and simpler alternative, INS appears to be a more attractive approach to building navigation systems.

2 CHALLENGES

Using INSs in real-world situations, however, is limited because its MEMS devices are susceptible to noise and gradual drifts that cause cascading errors. Because of this, most existing INSs integrate regular checking with access points with known positions such as satellites and Wi-fi routers to calculate the position of the mobile unit to compensate for these inaccuracies (Martin et al., 2006).

Another problem, which this study intends to address, is correctly classifying irregular movements. In this research, positive pedestrian

Ngo C., See S. and Legaspi R..
Improving Inertial Navigation Systems with Pedestrian Locomotion Classifiers.
DOI: 10.5220/0005242802020208
In *Proceedings of the 5th International Conference on Pervasive and Embedded Computing and Communication Systems* (PECCS-2015), pages 202-208
ISBN: 978-989-758-084-0

locomotion is defined as movements that include moving from one physical position to another on foot. Examples of these are walking, jogging, running, and climbing up and down the stairs. False pedestrian locomotion are movements that do not require moving from a position, such as standing. There are, however, some false pedestrian locomotion movements that can simulate movement from position, and these presents a problem to some existing INSs. These movements include walking-in-place, jogging-in-place, and running in place. It is important future INSs can correctly disregard false pedestrian locomotion movements to avoid cascading errors as the modules depend on each other as displayed in Figure 1. Similarly, it cannot be expected that users would not exhibit any form of negative pedestrian locomotion movements in real-world applications. An INS that considers in these negative movements will better suit mobile applications that plan to map user paths in an area.

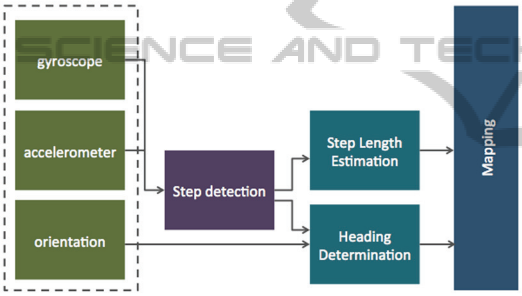

Figure 1: Conventional system flow of inertial navigation systems.

The main objective of this research is to solve this problem by creating an additional module in an INS whose role is to classify whether a user is making a positive or negative pedestrian locomotion movement. In the proposed solution, false pedestrian locomotion movements will be properly detected, thus false steps would be avoided. This will consequently affect the estimated path length of the user and is hypothesized to improve the outputs of the INS.

3 REVIEW OF RELATED LITERATURE

3.1 Pedestrian Locomotion Heuristics

There are currently no studies that have a separate module to classify positive from negative pedestrian locomotion, but there are some that have integrated similar measures in their step detection algorithms. In some studies like (Lee and Mase, 2001) and (Li et al., 2012), additional heuristics were implemented to prevent allowing false positive steps. These heuristics are hard-coded based on each study's preliminary data. As it is, more heuristics will need to be added to allow more movements.

Although the following research did not take into consideration a wider range of movements compared to this study, their heuristics were able to prevent certain negative pedestrian locomotion movements as positive.

3.1.1 Lag Parameter

In a study conducted by (Lee and Mase, 2001), a lag parameter was added in their step detection algorithm. With the lag, the system can supposedly check if the step taken is not a step but another body movement. It involves getting the z-axis of the accelerometer that is indicative of upward movements of the leg. The lag parameter is as follows:

$$\mathrm{lag} = \min_{j=0\ldots N}\left(\sum_{n=0}^{N} z(n)z(n-j)\right) \qquad (1)$$

where *lag* is the lag parameter, *N* is the window size, and *z(n)* is the z-axis value of the accelerometer at time *j,* which usually changes as the subject raises his leg.

The lag must be greater than a threshold to pass the heuristic. As can be seen in the equation, the study assumed that other body movements would have less activity in the accelerometer's z-axis, and that walking would induce peaks in the z-axis. However, walking-in-place would also express a high activity in the z-axis even though it is truly a false pedestrian locomotion movement.

3.1.2 Dynamic Time Warping

In (Li et al., 2012)'s study further used dynamic time warping (DTW) as an added filter to detect false steps. Aside from (1) checking if peaks and valleys pass a certain threshold, (2) peaks and valleys must also not be too short, or (3) too long (maximum of 1 second). Acceleration's peak and valley's magnitudes are also considered, where (4) the magnitude must be within a minimum of 0.2g, and a maximum of 2.0g.

With DTW, two more heuristics were formed. A fifth heuristic uses DTW to calculate the similarity of steps taken with the right leg, and similarity of steps taken with the left leg. In this condition, the similarity of the last step taken with the left/right foot and the current step taken with the left/right foot must be greater than a threshold. If the result is negative, a sixth heuristic compares the current left step with the next left step. If these two signal's similarity passes the threshold, the current left step would be considered a step. With this method, their step detection algorithm can tell the difference between a step taken while walking and a step taken while walking-in-place given that the two steps are taken after the other and the false step is just a momentary gap from a series of true pedestrian locomotion movements. However, their system can still possibly fail if the user continues to perform a false pedestrian locomotion movement.

After adding the DTW heuristic, the research recorded a drop in false positives (incorrectly processed false steps) from 29 to 14.

In the study, false negatives are more important than false positives. False positives can be further checked with the step detection algorithm. Even if a false step was considered a step in the pedestrian locomotion model, there is still the possibility that the false step would be detected as false by the step detection algorithm. The false negatives increased from 0.4 to 0.5. But as stated in the study, the benefits outweighed the disadvantages.

4 PROPOSED SOLUTION

This research proposes to create a separate module in the standard INS framework that will focus on classifying a movement as either false or true pedestrian locomotion movement. As shown in Fig. 2, the new module would operate first before the step detection module. If the module identifies a window of movement as false pedestrian locomotion, the succeeding modules would not process that window. If it does detect the window as true, the succeeding modules would operate normally. This would imply that the INS could

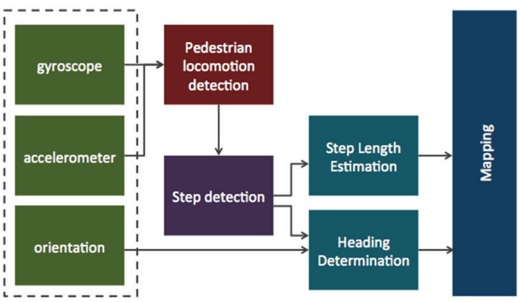

Figure 2: Proposed system of the research.

perform more efficiently should the new module classify well. On the other hand, a cascading error can transpire instead.

4.1 Inertial Navigation System

A simple INS would be created to compare the performance of a conventional INS against an INS with the pedestrian locomotion detection module. The modules are discussed below along with the algorithms and heuristics used in each.

4.1.1 Step Detection Module

The step detection module would detect steps from accelerometer signals once the pedestrian locomotion model determines that the user is performing a positive pedestrian locomotion movement.

The accelerometer signals would be scoured for a value greater than threshold α. In order to discard false peaks, a second threshold β is introduced. Threshold β is the minimum time gap between two steps. Before a step is identified, the time gap between the said step and the previous step must be greater than threshold β.

Both thresholds were determined after collecting user data.

4.1.2 Stride Length Estimation Module

The stride length estimation module would start calculating for the step length once the Step Detection Module has determined the user made a step. A linear model would be created as previous studies such as (Li et al., 2012) have shown before that a linear relationship exists between stride length and step frequency. This module would update the step frequency along with the Step Detection Module. A linear model would be generated after collecting data.

4.1.3 Heading Determination Module

This module would work side-by-side with the Stride Length Estimation Module after the Step Detection Module determines a step has been taken. It is responsible of approximating the direction the user is heading. In this research, the orientation y-axis data would be used to determine the heading. The values can range between 0° and 359°.

4.1.4 Mapping Module

The mapping module outputs a series of points indicating a user's traversal across a space. It would receive inputs from the stride length estimator module and heading determination module, and would have knowledge of the coordinates of the previous point. The coordinates of the initial point would be set to (0,0).

The new point would be calculated as:

$$x_{cur} = l * \cos(\alpha) + x_{prev} \quad (2)$$

$$y_{cur} = l * \sin(\alpha) + y_{prev} \quad (3)$$

where x_{cur} is the x-coordinate of the current point, y_{cur} is the y-coordinate of the current point, x_{prev} is the x-coordinate of the previous point, and y_{prev} is the y-coordinate of the previous point, l is the stride length, and α is the heading.

4.2 Pedestrian Locomotion Model

As the main component of the pedestrian locomotion module, the pedestrian locomotion model is a classifier that identifies movements as either positive or negative pedestrian locomotion movements. A discussion of how the model was created is written below.

4.2.1 Data Collection

In this research, 30 subjects will participate by performing 12 movements for data collection. Each subject should be at the age range of 19 to 49 years old, as a stable gait has been found across that age range (Thanh et al., 2012). On a similar note, the subjects should also be able-bodied. Every subject will perform each of the 12 movements for 5 minutes each. The 12 movements are composed of 3 positive pedestrian locomotion movements: (a) walking, (b) climbing down stairs, and (c) climbing up stairs; and 9 negative pedestrian locomotion movements: (d) turning, (e) standing, (f) swinging one's legs, (g) sitting, (h) twisting, (i) walking in place, (j) leaning on the heels and balls of one's feet, (k) doing random movements in place, and (l) bending. The random activity can be used to test the robustness of the model in terms of classifying unlisted movements in future research.

A Samsung Galaxy S2 phone was used to collect data. For this purpose, a mobile application was developed to collect sensor readings from the tri-axial gyroscope and tri-axial accelerometer at a rate of 100Hz. The phone was placed in the subjects's right-side pockets at the front. Placing the phone in the mid-section of the subject is strategic as it is the person's center of gravity, making it sensitive to movements made with the limbs. The position is also a typical location phones are placed in. The phone is limited to a specific orientation that faces the phone screen towards the thigh of the subject, and the top of the phone is pointed down.

4.2.2 Feature Modelling

The data entries would be grouped into windows of size 100. This window size is equivalent to a second worth of records, and will have an overlap of 50%.

Three features were extracted from each of the sensors's axes: mean, standard deviation, and energy. These features were extracted without removing the gravity factor from the readings, or applying any filter.

4.2.3 Model Generation

A C4.5 model and a support vector machines (SVM) model would be generated using WEKA's J48 and sequential minimal optimization (SMO) algorithms. The model would be used in the pedestrian locomotion detection module, and would determine if the person is performing a positive or negative pedestrian locomotion movement.

5 RESULTS AND DISCUSSION

5.1 Tests

Two kinds of test were conducted to evaluate the INS with and without the prediction module: the square route test, and the multi-activity square route test. The tests were carried out by six subjects, wherein they were limited to follow a marked route, to execute movements as instructed to them, and to only bring the phone out at the beginning and end of each test. The subjects were allowed to walk on their own natural regular pace.

Square Route Test: The square route test is a 20m walk that is composed of four five-meter sections that are orthogonal after one another. The route is purely positive pedestrian locomotion, and is intended to test the prediction model's performance in a situation where an INS without a prediction module will perform perfectly. Another factor to analyse is the model's ability to classify "walking while turning" from "turning in place".

Multi-Activity Square Route Test: The multi-activity square route test is similar to the square route test but introduces negative pedestrian locomotion in every corner. The routine, which is presented in Figure 3 begins with 1) a five meter walk, 2) five seconds of standing, 3) five meter walk after a perpendicular turn, 4) five seconds of walking-in-place, 5) five meter walk after a perpendicular turn, 6) five seconds of bending, 7) five meter walk after a perpendicular turn, and 8) five second of twisting. Since walking five meters usually takes 3.5 to 5 seconds, this test is the more balanced in terms of number of the positive and negative pedestrian locomotion movements. This makes this test a good way to evaluate the INS with a prediction module.

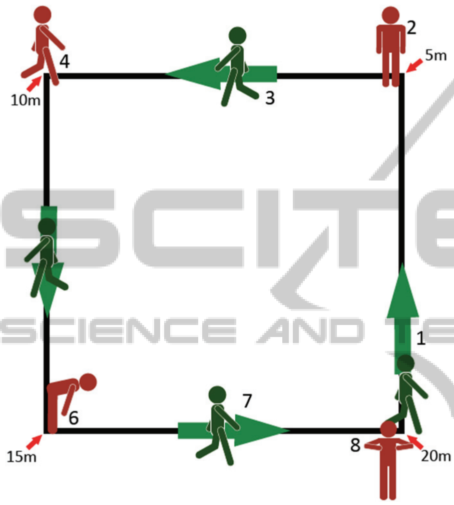

Figure 3: The multi-activity square route test is composed of negative and positive pedestrian locomotion.

5.2 Prediction Module

For the square route test, the recall of positive and accuracy are the same because it is a purely positive activity. The INS without a prediction module also has a 100% recall and accuracy for the same reason.

As can be seen in Table 1, the J48 and SMO models performed well. A closer look at the J48 results reveals that three subjects had data that were all correctly classified, while the other three had one misclassification each. The SMO model correctly classified all instances as positive except for one misprediction.

The multi-activity square route shows a lower accuracy and recall for both models. It is, however, important to note that both models have an acceptable recall on positive. In this research, the recall on positive locomotion is more important. Accidentally predicting a negative locomotion as positive does not automatically mean that steps will be detected; the possibility of the step detection module to not detect steps is still open.

Table 1: Prediction module results for INSs with and without a prediction module.

		Recall on Positive	Recall on Negative	Accuracy
Square Route	J48	97.03%		97.03%
	SMO	99.01%		99.01%
Multi-Activity Square Route	w/out	100.00%	0.00%	48.51%
	J48	87.72%	67.77%	77.45%
	SMO	90.35%	71.07%	80.43%

5.3 Step Detection Module

It is expected that the step count error in the step detection module will decrease if the INS will use a prediction module. Table 2 shows the step count error produced by the INS with and without a prediction module.

The square route test reveals that the INS without a prediction module performs better, only mispredicting seven steps. The INSs with the prediction modules had a higher error, with the J48 model missing 12 steps and the SMO eight steps. This suggests that the additional module allowed more false negatives than an INS without a prediction module.

But the multi-activity square route test presents a different outcome where the INSs with the prediction module now performs more accurately in terms of step count error. Both prediction models elicited a significantly lower step count error. This indicates in exchange of versatility when it comes to negative locomotion, some false negatives were allowed to be made. But given the difference in errors, the benefits of having a prediction module outweigh the disadvantages. INSs with the module are more adaptable in terms of allowing the subject to perform negative pedestrian locomotion.

Table 2: Step detection module results for INSs with and without a prediction module.

		Actual # of Steps	Estimated # of Steps	Error
Square Route	without	188	181	3.72%
	J48		176	6.38%
	SMO		180	4.26%
Multi-Activity Square Route	without	193	296	34.80%
	J48		233	17.17%
	SMO		233	17.17%

5.4 Stride Length Estimation Module

As with the step detection module, the error in total distance travelled will also be assessed for the stride length estimate module. The length errors of the INSs with and without a prediction module are presented in Table 3.

Similar to the results of the step detection module, the error result is based on the kind of test the INS undergoes. This is because the stride length estimation module's result is also based on the preceding step detection module; that is the total distance travelled is directly proportional to the step count. Given this, the INS without the prediction module performed better in the square route test, while the INS without it had a better accuracy in the multi-activity square route test. Though there is a clear advantage when the basic INS is used in a purely positive activity, using a classification model introduces versatility to the system.

Table 3: Stride length estimation module results for INSs with and without a prediction module.

		Actual Length (m)	Estimated length (m)	Error
Square Route	without	120	117.98	1.69%
	J48		114.70	4.41%
	SMO		117.29	2.26%
Multi-Activity Square Route	without	120	193.67	61.39%
	J48		151.97	26.64%
	SMO		161.65	34.71%

5.5 Mapping Module

The final output of the INS is the route the user has traversed. For both tests, the INS with the prediction module fared well. Both J48 and SMO prediction modules came up with close results, one of which is shown in Figure 4. In the figure, the route in black is the actual route and the route in yellow is the estimated route of the INS. Although the distance travelled was accurately measured, the orientation was not determined properly, thus resulting to an incorrect map.

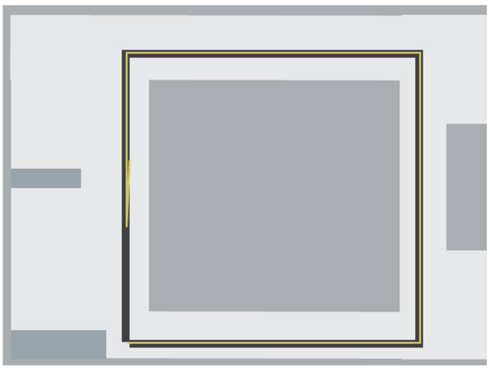

Figure 4: Map generated using J48 and SMO as pedestrian locomotion classification models.

It is also important to note that the INS used in this research worked well with the given route because it is limited to perpendicular orientations. The heading determination module used in this research is especially basic and still needs improvement.

6 CONCLUSIONS

This research was able to present that a J48 and SMO pedestrian locomotion classifier can increase the over-all performance of an INS. The step detection and stride length estimation module also benefited from the prediction model especially with experiments that have negative pedestrian locomotion activities.

In conclusion, the results have shown that adding a pedestrian locomotion module allows an INS to be more versatile. An INS with a prediction module can handle negative pedestrian locomotion activity, while a normal INS will require users to walk continuously and maintain a low sensor activity to prohibit a negative pedestrian locomotion activity to be falsely considered a step. And as negative pedestrian locomotion activities are inevitable in real scenarios, a prediction module presents an adequate solution to this INS problem.

Further research can delve into further testing the system for its capabilities and weaknesses. Additional work still needs to be done to improve the heading determination module of the system, which is currently limiting the system to specific routes. Future studies can also focus on employing additional sensors to improve and compensate for the MEMs inherent noise.

ACKNOWLEDGEMENTS

This research is made possible with funding from the Philippine government. The researchers would like to thank the Department of Science and Technology's Engineering Research and Development for Technology (DOST-ERDT) program for its incalculable support for this study.

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