

Localization system for pedestrians based on sensor and information fusion

Ricardo Anacleto, Lino Figueiredo and Ana Almeida

GECAD - Knowledge Engineering and Decision
Support Research Center,

School of Engineering - Polytechnic of Porto, Porto, Portugal
{rmsao,lbf,amn}@isep.ipp.pt

Paulo Novais

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

Abstract—Nowadays there is an increase of location-aware mobile applications. However, these applications only retrieve location with a mobile device's GPS chip. This means that in indoor or in more dense environments these applications don't work properly. To provide location information everywhere a pedestrian Inertial Navigation System (INS) is typically used, but these systems can have a large estimation error since, in order to turn the system wearable, they use low-cost and low-power sensors. In this work a pedestrian INS is proposed, where force sensors were included to combine with the accelerometer data in order to have a better detection of the stance phase of the human gait cycle, which leads to improvements in location estimation. Besides sensor fusion an information fusion architecture is proposed, based on the information from GPS and several inertial units placed on the pedestrian body, that will be used to learn the pedestrian gait behavior to correct, in real-time, the inertial sensors errors, thus improving location estimation.

Keywords—*Pedestrian Inertial Navigation System, Indoor Location, GPS, Force Sensors, Sensor Fusion, Information Fusion*

I. INTRODUCTION

The ability to locate an individual or an object can be exploited to provide information to help or to assist in decision-making. For instance to help people with visual impairments [1], to support a tourist guide in an exhibition [2] or in a shopping [3], navigation systems for armies [4], healthcare applications [5], among others. The major limitation of these systems is related to retrieving pedestrian location in indoor or more dense environments. Retrieving location in an open environment, with an acceptable accuracy, is relatively simple using a GNSS (Global Navigation Satellite System) (like GPS, GLONASS, etc.). However, GNSS signal isn't available inside buildings, in urban canyons, in the underground, underwater and in dense forests.

Developing complementary localization technologies for these environments would unleash the mentioned applications capabilities. For example, inside an art gallery if the application knows the tourist current location it can recommend artworks to view and learn more about the tourist profile.

Actually there are already some proposed systems that retrieve indoor location with good accuracy [6] [7]. However, most of these solutions require the existence of a structured environment, which made them difficult to be deployed over large buildings, with very expensive implementation costs

since it needs a location-fingerprinting approach that is labor-intensive and vulnerable to environmental changes. This can be a possible solution when GNSS aren't available, but only indoors, since in a dense forest this kind of systems doesn't exist or work. Retrieving location on this type of terrain can be very useful for location knowledge of a fireman's team.

To avoid structured environment limitations, pedestrian Inertial Navigation Systems (INS) are being studied and will be discussed in section II.

Typically, an INS uses a computer, motion sensors (accelerometers) and rotation sensors (gyroscopes), among others, to continuously calculate via Pedestrian Dead Reckoning (PDR) [8] the position, orientation and velocity (direction and speed of movement) of a moving object.

These sensors are based on Micro Electro Mechanical Systems (MEMS) that are small and low-weight, which is perfect for embed on person's clothes or shoes. Unfortunately, large deviations of these sensors can affect performance, as well as the various ways in which a human can move, so this is the INS's big challenge: correct the sensors deviations.

With this type of system individual movements information can be obtained independently of the building infrastructure. However, some systems in literature [9] [10] propose INSs assisted by Wi-Fi, RFID, map matching, etc. to improve its accuracy. However, these hybrid approaches still need an implemented infrastructure to properly work and don't work on urban canyons, dense forest and in indoor environments.

Since retrieving location without using a structured environment remains an open research problem, this work describes our proposal for a pedestrian INS composed by several IMU (Inertial Measurement Unit) composed by sensors like accelerometer, gyroscope, force sensors, barometer and heart rate. These IMUs are spread along the pedestrian body to improve the system accuracy by using these data sources.

To integrate all the sensor data an information fusion algorithm will be developed, which will also learn the pedestrian gait patterns to correct in real-time the sensors errors. It estimates pedestrian location without the need of external systems, working in indoor environments as well as in dense ones where a GNSS isn't available.

The system hardware, software and the obtained results are described in more detail in section III. Finally some conclusions and future work are presented in section IV.

II. PEDESTRIAN INERTIAL NAVIGATION SYSTEM

In this section some pedestrian INS insights and systems will be presented. Since the users of this type of system are on foot a study about human gait is discussed. Finally, since our proposal uses force sensors placed on the foot plant, a study about the force applied on a foot's plant will be presented.

Unfortunately, pedestrian INSs are not able to ensure that the geographical location is accurate within a few meters. As result, location and orientation errors tend to grow unbounded. In fact, although these deviations may be small for every millisecond, the location error caused by a sustainable use of the system can exceed one meter in 10 seconds [11]. These estimation errors occur mainly during starts, stops, sharp turns and walking on inclines.

Pedestrian INS accuracy normally ranges from 0.5% to 10% of the total traveled distance, but these numbers strongly depend on the implemented algorithm, on the employed inertial sensor technology and on the tests environment. It works in 2D and 3D environments, however errors in Z-direction (earth gravity) are usually higher. The location errors are also strongly coupled with the heading errors via the true (relative) location. A heading error of 0.5° gives a relative position error of 1% of the traveled distance. However, if the user walks back the same distance the location errors, normally, are canceled out.

An INS is composed by one or more IMU. Typically an IMU contains three gyroscopes and accelerometers, which report angular velocity and linear acceleration respectively.

Accelerometers measure the linear acceleration of the system in the inertial reference frame, this means that measurements are relative to the moving system (since the accelerometers are usually fixed to the system and rotate with the system, they are not aware of their own orientation). Gyroscopes measure the angular velocity of the system in the inertial reference frame. By using the original orientation of the system in the inertial reference frame as the initial condition and integrating the angular velocity, the system's current orientation is always known.

To obtain height information a barometer is typically used. It measures atmospheric pressure and the height is determined according to the sea level atmospheric pressure. This pressure decreases at altitudes above sea level and increases below sea level.

Magnetometers are used to obtain the north direction and then estimate the moving direction. However, they are subject to strong magnetic disturbance such as power lines, computers, and various metal/steel objects and structures. When a magnetic compass is coupled with a gyroscope, the magnetic disturbances can potentially be detected and corrected, but the tuning of such filter can be extremely difficult.

Since an INS can be composed by several sensors it is very important to implement sensor fusion techniques. This includes algorithms that can interpret the sensors information and thereby determine the individual location.

Normally to estimate the person location, an INS uses a set of mechanization equations to convert the IMU measurements into useful position, velocity and attitude information. This set

of mechanization equations is based on the human gait cycle and involves three phases:

- Detect a step (using the accelerometer signal) - once a step is declared, the acceleration signal is analyzed to detects the type of step, *i.e.* forward or backward;
- Estimate the step-length - the principles of inertial navigation are simple, the accelerometer data is mathematically integrated to provide changes in velocity;
- Estimate heading - normally the data from a magnetometer, a gyroscope and an accelerometer are fused in order to estimate the heading.

While the quality of inertial sensors is a deciding factor for the performance of an INS, their placement on the user's body is also a very important factor. Several different placement of the sensors were already tested, *e.g.* waist [12], trunk [13], leg [14], foot [15] or even the head [16]. The waist or trunk locations are probably the least intrusive IMU placements and also the most reliable position for heading estimation [17] since it is near the user's center of gravity. However, the sensors placed on or inside the user's foot usually have the best results as the application of Zero velocity UPdaTe (ZUPT) strategy, which reduce drift after integrating accelerations [18], works better.

To compensate INS errors Jirawimut [19], Lee and Mase [20] and Godha et al. [15] calibrate PDR parameters, step size and magnetometer bias, using the GPS signal when the user is on outdoor environments to use them in indoor ones.

One of the best approaches to mitigate some of the gyroscope errors was proposed by Castaneda and Lamy-Perbal [12], which is an AUPT (Angular Update) algorithm based on the ZUPT concept. Ladetto et al. [13] tested two INS prototypes to estimate orientation, one based on a gyroscope and the other on a magnetometer, and concluded that the best approach is to use a combination of sensors since each one have their strengths and weaknesses.

Another difficulty encountered when developing a pedestrian INS is the stance phase detection. To make it easier and more reliable Hamaguchi [14] has introduced wearable electromagnetic sensors and push button switches attached to the user's heels. This has improved the stance detection so much that Bebek et al. [21] also implemented a similar technique. In this case they 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 position calculation. Compared to the other presented systems the inclusion of a tactile sensor improves the step detection. With stance phase comes a good opportunity for zero velocity reset.

Each one of the presented systems has their strengths and weaknesses and their performance can't be compared since each test case scenario is different. In a pedestrian INS test several variables influence the final result, as is the case of the pedestrian and the test environment, like the type of magnetic disturbances, type of floor and if it is wavy or flat, sensors quality, total distance walked, type of turns, among others. One variable that has the most influence on the results quality is the step cadence, since there is more errors when the user is moving more slowly.

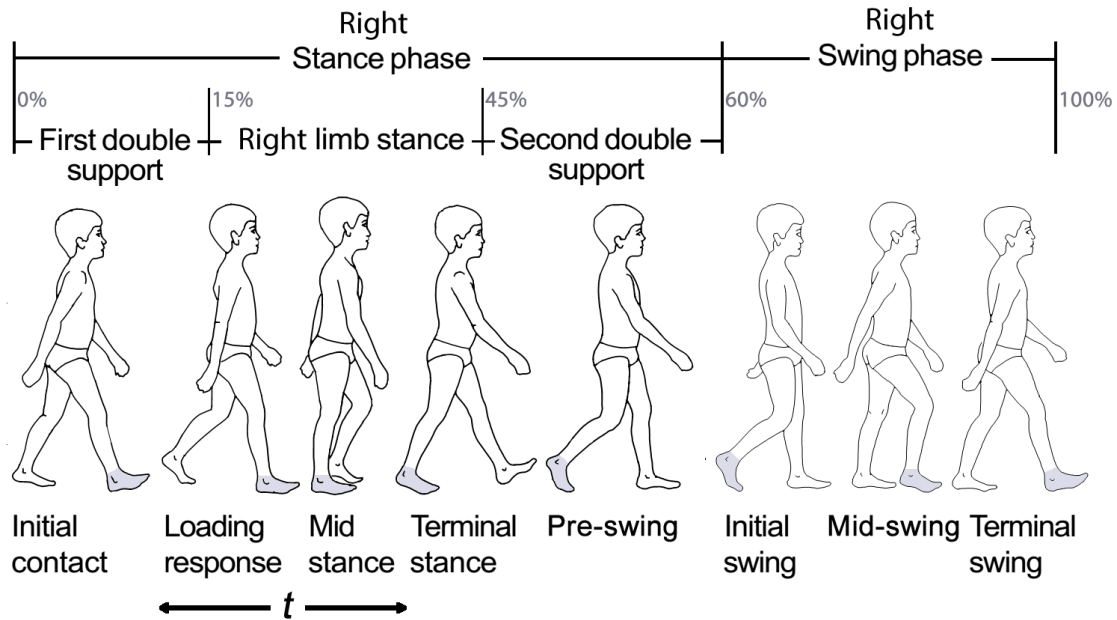


Fig. 1. Human gait cycle

A. Human Gait

Since an INS attempts to estimate the stride length, in this section, a theoretical explanation of the human gait behavior is performed. Human gait represents a movement pattern that repeats itself at each step and enables the transportation from one location to another [22].

The translation of human gait occurs via a series of events that repeats after each new contact of the heel with the ground (initial contact). These cyclical events allow the shift of the body support from one member to another. Thus, as the body moves, a member serves as a source of support and the other to advance until it contacts the ground. To transfer the weight from one member to another, both feet remain in contact with the ground [23]. This sequence of events is named gait cycle and is represented in Fig.1.

The human gait cycle is divided into two phases designated stance phase and swing phase. During the stance phase, the foot is in contact with the ground, whereas in the swing phase the foot is not in contact with the ground and the leg is moving until the same foot touches, again, the ground. In a normal step cycle the stance phase represents 60% of the time and the swing phase represents 40% of the time.

The stance phase is divided into three separate phases: first double support, in which both feet are in contact with the ground; single limb stance, when one foot is swinging and the other is in contact with the ground; and finally the second double support, when both feet are again in the ground.

It should be noted that the nomenclature in Fig.1 refers to the right side of the body. The same terminology would be applied to the left side. For a normal person this represents half a cycle. Thus, the first double support for the right side is the second double support to the left and vice versa.

Whenever there is a double support the body weight is transferred from one member to the other. The two moments

of double support, in a gait cycle, coincide with the time when a member is starting and the other is ending the stance phase. It should be noted that less time spent in the double support phase represents a higher walking speed [23]. When a person increases the step rate, the duration of the double support decreases and it is null if the person is running.

The loading response phase represents the interval at which the body weight is transferred to the member that will serve as support. In this interval the foot is completely in contact with the ground. The mid-stance phase begins when the foot, which was previously serving as support, is no longer in contact with the ground and moves forward. So, the body support is only performed by one of the members. The terminal stance phase begins when the heel is raised and ends when the opposite foot begins its contact with the ground. During this phase the body weight moves to the foot in analysis (right foot).

The pre-swing phase is the terminal phase of the double support and begins when the opposite leg (left in this case) comes in contact with the ground and ends when the foot in question (in this case the right) is no longer in contact with the ground. During the pre-swing the body weight is fully transferred to the foot that will serve as support.

The initial swing phase starts when the foot is no longer in contact with the ground and continues until the maximum flexion of the knee occurs, *i.e.*, it is the beginning of the lifting motion of the leg. The mid-swing phase begins after the knee maximum flexion and ends when the tibia is vertical. This phase is the end of the leg lifting motion. The terminal swing phase is the preparation for the heel to contact the ground.

B. Force Applied on Foot Plant

To distinguish more accurately each phase of the gait cycle, the force that is applied to the foot plant could be analyzed. By knowing the force that is being applied to the foot's plant the step detection can be significantly improved, as well as,

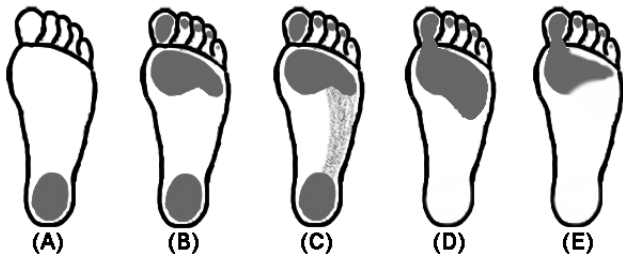


Fig. 2. Force applied on the foot for each stance phase sub-phases

the correspondent estimation of the traveled distance. Fig.2 presents the force sequence (the applied force is shown in grey) in the foot plant during a normal gait cycle, it can be seen that the central region of the foot has almost no participation in the step.

The initial phase (A), which represents the first contact of the foot with the ground, and the final stage (E), which represents the last contact of the foot with the ground, are the stages that represent the most significant force on the plantar surface especially on the heel or in the front area. This force is much more significant than in the stance phase (B and C). Also, on stairs ascent and descent, the force is concentrated mainly on the foot front and in the hell the force is negligible.

Fig.2 is directly related to the sub-phases that occur during the stance phase, wherein:

- (A) Represents the initial contact of the foot with the ground;
- (B) Represents the time at which the response to the load occurs;
- (C) Represents the mid stance phase where support is being made solely by this foot;
- (D) Is the terminal stance phase;
- (E) Represents the pre-swing phase.

After these phases the foot is no longer in contact with the ground, since it had started the swing phase.

III. PROPOSED ARCHITECTURE

To overcome typical INS disadvantages our proposal includes force sensors to potentiate a better stance phase detection. Also, another claim of our proposal is the capability to retrieve pedestrian location everywhere, independently of the environment and only based on the sensors that are placed on the human body. To achieve this objective a hybrid system based on GPS, INS and other technologies/techniques such as, force sensors, heart rate sensor and probabilistic/learning gait algorithms, is proposed.

The system is composed by two parts which will be discussed on the next sub-sections:

- Hardware - consists on Body Sensors Units (BSU) distributed in the lower limbs (legs and hip area) to collect movement's data. These BSUs communicate, through a ZigBee wireless network [24], with a Body

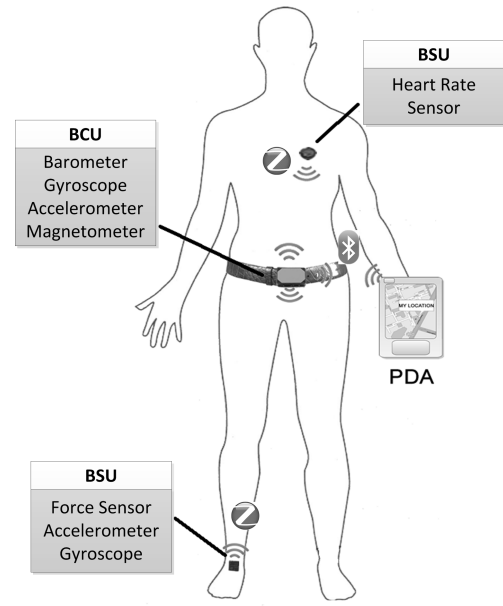


Fig. 3. Sensor distribution on the human body and wireless communication

Central Unit (BCU) that implement part of the algorithms. More details can be seen in section III-A;

- Software - integrates the information from the sensors (sensor fusion) and thereby tries to estimate the person's location. After the sensor fusion an information fusion architecture gathers the information from the several BSUs spread along the body to compute a more accurate walking path estimation. This information fusion is constituted by learning and probabilistic algorithms that learn the user step pace to correct, in real-time, possible sensor deviations. More details can be seen in section III-B.

This project has two main goals, the first one is to have an accuracy, of the estimated location, between 90% and 95%, or in other words, per each 100 meters traveled the system must have an error between 5 and 10 meters. The second goal, is the delay between the sensor readings and the exhibition of the current user location. To be considered real-time this delay should be less than 2 seconds.

A. Hardware

Small BSUs were distributed by the lower limbs (foot and hip area) to collect information about body movements. Preferably, in the future, it is wanted that the sensors can be integrated into person's clothes and shoes, to be easier to use and more imperceptible to the user. The BSU data is sent to a BCU that handle the calculations needed to estimate, in real-time, the person location. As can be seen in Fig.3 these modules are placed around the body and are connected through a wireless sensor network. The BCU module also sends real-time data from the INS system to a mobile device via a Bluetooth connection.

The system is composed by three BSU modules totally developed by the authors. The first one, placed on the foot and represented in Fig.5 is constituted by a force sensor, a



Fig. 4. Force sensors position and force applied on the foot

gyroscope and an accelerometer. The second one, which is also the BCU, is composed by a gyroscope, an accelerometer, a magnetometer and a barometer in the abdominal area. Finally the third one is composed by a heart rate sensor in the chest area. Force sensors were included since they are very important to detect when the user touches his feet on the ground, as well as, the correspondent contact force, which combined with the accelerometer (used to obtain the step acceleration) can improve the accuracy of step length estimation.

The force sensors were placed on the foot plant as shown in Fig.4. This force sensors disposal allows knowing if the foot is in contact with the ground, from the first contact of the heel with the ground (where force sensor A is located) until the front of the foot is no longer in contact with the ground (where force sensor B is located), in order words, during the entire stance phase as shown in Fig.1.

The gyroscope, accelerometer and magnetometer are valuable to get the body travel direction. The barometer on the abdominal area, is used to get the user elevation. The heart rate data is useful, in combination with the other sensors data, to know more precisely the user activity (*e.g.*, walking, running, etc.). This sensor can improve the system precision, since when a person is traveling faster the heartbeat is higher than when a person is only standing-up.

The wireless sensor network is based on the ZigBee protocol which is a low-cost, low-power wireless mesh network, providing the ability for devices to run a long time on inexpensive batteries in a typical monitoring application.

In order to successfully implement this wireless network and the corresponding sensors there are some “open problems” that must be solved. These problems include issues related to deployment, security, calibration, failure detection and power management.

B. Integration Modules and Sensor Fusion

In the previous section the sensory set, the wireless communications and the data acquisition procedures at hardware level, were presented. But beyond it, this sensory set requires the implementation of a sensor fusion.

To reduce INS errors inertial sensors data must be integrated. This integration software is represented in Fig.6 and has two main components, which are a “Low Level Integration Software” (subsection III-B1) and a “High Level Integration Software” (subsection III-B2). The first one, which is the one that this work pretends to explore in more detail, is composed by a preprocessing INS to remove sensors noise and a Filtering and Navigation Algorithm.

In order to estimate the user displacement an algorithm, based on the traditional INS approaches, was implemented. It

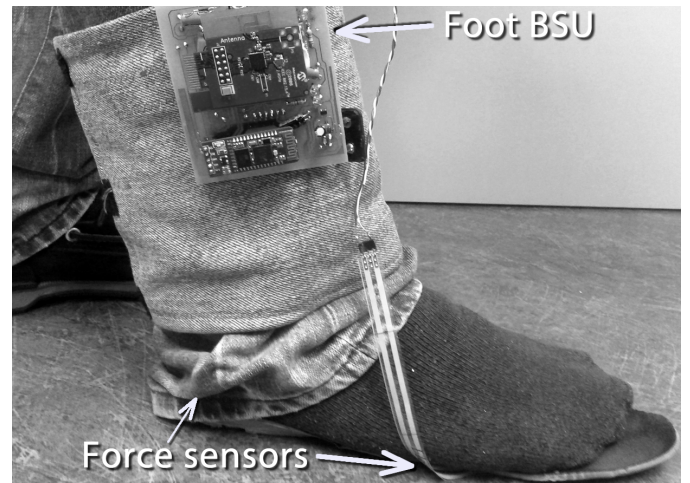


Fig. 5. Developed foot body sensor unit

was designed to improve the common errors in order to have the lowest possible error.

1) *Low Level Integration Software*: To estimate the traveled distance it was implemented the algorithm represented in Fig.7. First of all there is a setup procedure, when the device is stationary, that calculates the offset based on the sensors noise. Since the module is placed on the pedestrian ankle its rotations can't be negligible. So this algorithm uses the gyroscope to estimate the orientation of the accelerometer in order to project accelerations into the navigation coordinate system, and this data is corrected due to the effect of gravity. Then the data is corrected with the estimated offset and then filtered by the Threshold Filter. Finally, to estimate the displacement a Kalman filter based on the Wiener-process in the white-noise jerk version was used.

To verify if the pedestrian is stationary an acceleration data threshold is used. If the device is stationary (acceleration values are within the bounds of the threshold filter) speed is set at zero, in other words the ZUPT technique is applied which is used to mitigate the drift problem. The integration of inertial measurement is only performed during the swing of legs and the velocity errors can be reset at each step since when INS is stationary the true velocity must be zero. This is a technique that a lot of the studied systems use but only using accelerometer data. However, the proposed system uses force sensors to improve step prediction, since they can provide information about the moment when the person puts the feet on the ground and the respective contact force.

Also, the application of ZUPT and other techniques during the stance phase eliminates useful information because, as can be seen in Fig.1, when the foot comes into contact with the ground there is small movement of the foot to start the Loading Response Phase, and when the foot enters the Terminal Stance Phase it is still in contact with the ground but some motion still exists. The correct use of ZUPT occurs when it is applied only during the interval t as shown in Fig.1.

The aggregation of the force sensors data with the acceleration data allows the achievement of more useful information and eliminates false detections. Fig.8 presents the algorithms used to detect when the foot is stationary. The algorithm

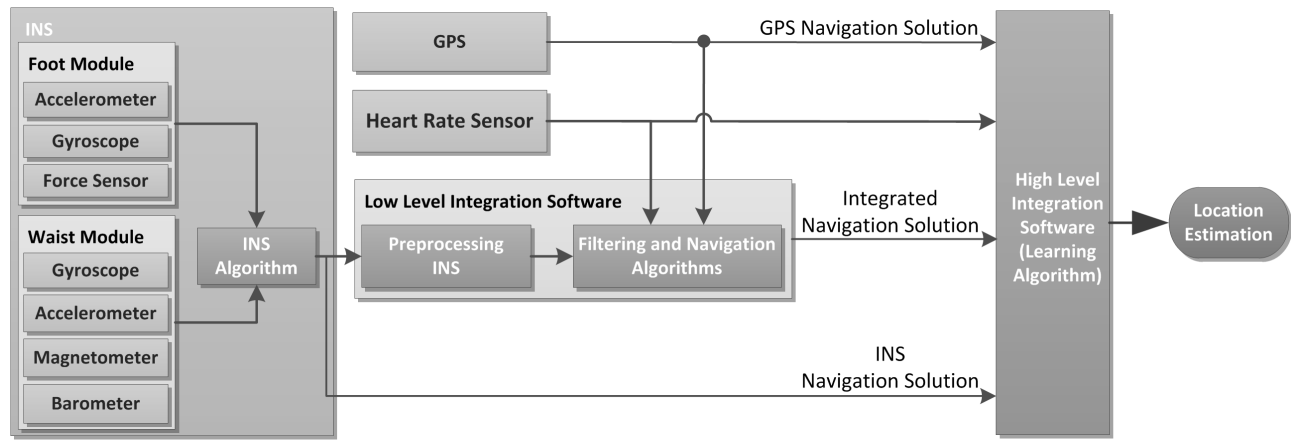


Fig. 6. Proposed software architecture

a) is only based on accelerometer data (as the typically pedestrian INS use) and b) is our proposal that includes both accelerometer and force sensors.

Algorithm a) analyzes the acceleration samples of the current and the previous time instant. This analysis allows to not detect the foot as stationary when the foot is in the swing phase. However, our approach (algorithm b) analyzes the acceleration and the force sensors data in the current moment. With this data fusion the algorithm doesn't detect false stance phases when the foot is already on the swing phase.

In algorithm b) the data from the two force sensors is combined into one. In this stage the combined force will be different from zero when a force is applied to the heel until no force is applied on the front of the foot. If the combined force is not zero the acceleration is defined to a predefined value of $1g$ and the threshold to the minimum value. If the combined force is zero the acceleration threshold is computed and compared with the real acceleration to estimate the step length.

In the INS algorithm it was also applied the AUP technique that resets the angle value to the value that was gathered during the setup procedure.

There is a problem to deal with in the near future, derived from the project complexity, that is the delay between the real location and the processed one (that appears on the user mobile device). The result data returned by this module will be the data required by the mobile platform to compute/correct the person location.

2) *High Level Integration Software*: In order to reduce the errors provided by MEMS the data from the foot module, waist module and heart rate sensor must be integrated. Each one of these modules will have a certainty degree associated to it. This is important since each place on the human body (*i.e.*, waist, foot, etc.) has its downsides and benefits on each phase of the human gait cycle. With this in mind a degree of certainty will be given to each sensor placed on the person's body. Through this information fusion we believe, from our previous and current experiments, that the system accuracy can be improved.

Also, a probabilistic algorithm learns the walking/moving

behaviors in each type of environment for correcting, in real-time, the data gathered from the sensors. This algorithm will be based on supervised learning, which specifies that a training data is created and it is analyzed to produce some inferred function, normally named as classifiers. The result of this algorithm is the estimated user's location.

Walking is a cyclic activity, which represents a cyclic pattern of movement that is repeated over and over, step after step [23]. So, these walking patterns can be extracted in the learning phase and used as a reference model. These patterns will be learned, over time, when GPS is available (with very good signal) or in a controlled phase where from a set of exercises the gait analysis is obtained. Resuming, the system will be always learning the step pattern and will be improving it over time. The inertial sensors data correction will be performed in real-time when GPS isn't available.

In terms of data integration strategies a Loosely Coupled and a Tight Coupled Approach will be adopted. The first one, which can be faster but more sensible to errors, will be important when GPS signal isn't available and the system will only rely on the INS, the heart sensor and the probabilistic algorithms. The Tight Coupled Approach is the one that results on the Integrated Navigation Solution and it will be important to improve the system accuracy when it is learning the person's step pattern. In this learning phase both strategies will be working, since the system could learn from the Tight Coupled approach the errors given by the INS navigation solution.

Besides the learning module, another module (API) will be developed to integrate the data from the different sources. This API will be responsible to retrieve the current user's location estimated by the GPS/INS localization system.

A mobile device with Android operating system will be used in this case, since the research team already has experience with this operating system and its platform is very flexible to be used with sensors. The modules that constitute the High Level Integration Software are already being studied and we hope to have interesting results very soon.

C. Obtained Results

In this section we will discuss the results of our experiments and compare our proposal with the typically used

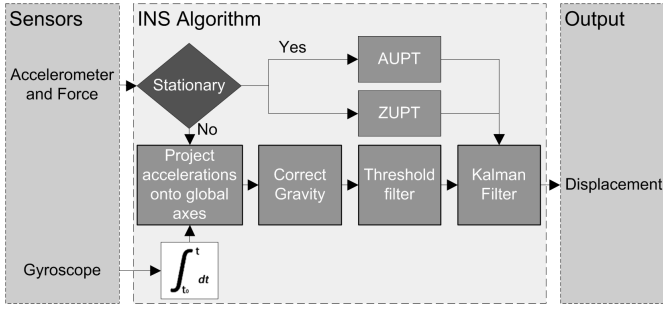


Fig. 7. Distance Displacement Estimation Algorithm

algorithms that use only the accelerometer data to detect if the pedestrian is stationary.

In order to validate the BSU module an experiment was performed. It consisted in a straight line ten step walking and the produced data can be seen in Fig.9. In this figure is represented the data retrieved from the accelerometer and the two force sensors over time, it can be seen that sensors data is correlated between each other.

The solid line represents the acceleration sensed on the ankle, the dashed line represents the data from force sensor A and dotted line represents the data from force sensor B. As can be seen the values of force are zero, or almost zero, when the foot is moving (when there is higher variations in acceleration values), and when the foot is on the ground, sensor A goes first to a high value and then sensor B goes to a high value, as expected. This high value occurs when the foot touches the ground. With the fusion of the two force sensors data a more accurate step detection was achieved.

To compare our method with the typical INS approach, that uses only the accelerometer data to detect if the pedestrian is stationary, an experiment was performed that consisted of a straight line walking with a total distance of 10 meters. For this scenario a total of 60 samples were processed for each algorithm, where three types of walking (slow, normal and fast) were tested.

The obtained results, from both approaches, are presented in Table I. The addition of the force sensors has reduced the average error from 9.2%, of the typically used Kalman filter, ZUPT and AUPT algorithm, to 7.3% which represents an improvement of about 26%.

TABLE I. ERROR FOR A TRAVELED DISTANCE OF 10 METERS (IN %)

| Technique | Slow | Normal | Fast | Average |
|--------------|------|--------|------|---------|
| Normal | 13.7 | 8.1 | 5.9 | 9.2 |
| Our proposal | 9.1 | 8.0 | 4.9 | 7.3 |

Thus, it can be concluded that the distance estimation using force sensors is more accurate, which translates in a significant reduction of the accumulated error. That is, the addition of force sensors allows a better detection of the stance phase (interval t shown in Fig.1), unlike the accelerometer only approaches that easily detects it earlier or later. Even if this deviation is short, this duration corresponds directly to the removal of useful information and therefore a larger error in the estimated distance.

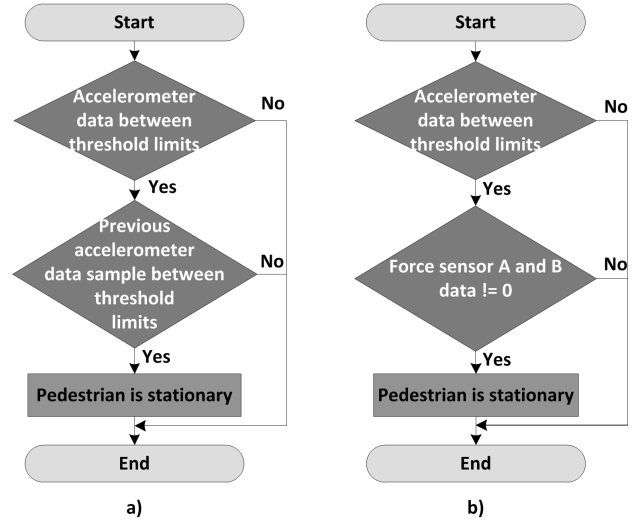


Fig. 8. Algorithms to detect if the pedestrian is stationary, a) using only the accelerometer data; b) proposed approach that uses both accelerometer and force sensors data

It should be noted that a less accurate stance phase detection leads to the introduction of errors at each stride on a journey that can lead to inaccurate estimations, hence evidencing the importance of this approach.

Thus it can be said that the improvement in the detection of interval t has a great importance in reducing the error of the estimated distance. These results are considered satisfactory and it was also found that the error decreases as the gait is faster. The results also have shown that the proposed algorithm is better in a long term use.

To enhance these results we are working on the fusion of the information retrieved by all the sensory set. This is important since each module has its strengths and weaknesses on each phase of the human gait cycle. In conjunction with the learning algorithms it is expected to improve the overall system accuracy, in order to it be usable on a daily basis.

IV. CONCLUSION

The development of an accurate, inexpensive, small and unobtrusive localization system to be used by persons, when they are on foot, in environments where GPS is unavailable can be a huge challenge. Many approaches already have been proposed, but most of them rely on a structured environment that usually is unfeasible to implement and others don't provide the necessary accuracy.

Our proposal uses only a minimal set of small sensors and exploit the available data to the fullest extent to provide an acceptable level of performance. The described solution uses small MEMS spread along the body, where a heartbeat and force sensors are included to improve system accuracy. All these sensors are integrated using some proven traditional sensor fusion algorithms (strap down noise reduction, Kalman filter and error modeling) and some newer ideas, probabilistic algorithms to learn the person walking behavior and certainty degree level given to each sensor at each gait cycle phase.

This work enhances the INS results by using an algorithm

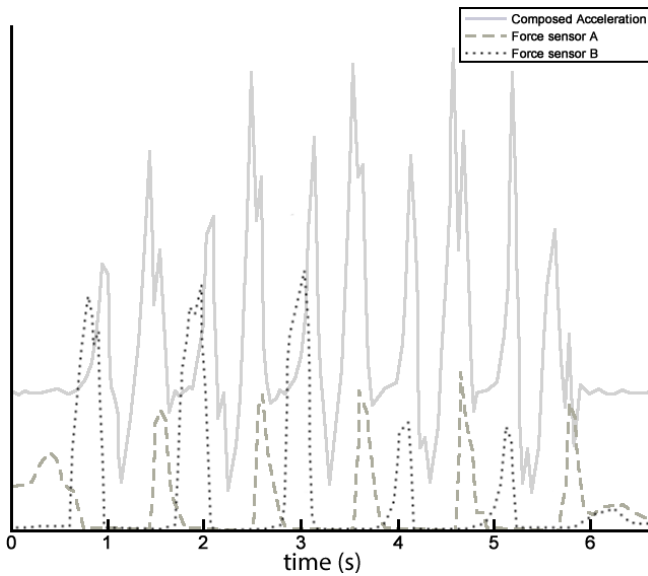


Fig. 9. Accelerometer and force sensors data for a 10 step path

based on force sensors. The stance phase detection was improved as so the estimation of the traveled distance.

The proposed approach is very interesting since after tuning the concept, it leads to acceptable results. Compared to the traditional method that detects stance phase using only acceleration data, the force sensors plus acceleration data improved the traveled distance estimation error by 1.9%. The most notable differences were in the slow walking where the proposed approach has an estimation error of 9.1% which is 4.6% less than the traditional approach. This can be considered to be very good results, given the MEMS sensors quality.

In future work we intend to present the results of our experiments for different information fusion strategies. With this fusion more accurate results can be achieved by using the different information sources. Each one of this source has its strengths and weaknesses, so it can be explored to define a certain degree of certainty at each gait cycle phase.

ACKNOWLEDGMENT

This work is funded by National Funds through the FCT - Fundação para a Ciência e a Tecnologia (Portuguese Foundation for Science and Technology) within project PEst-OE/EEI/UI0752/2014. The work of Ricardo Anacleto is supported by a doctoral grant by FCT SFRH/BD/70248/2010.

REFERENCES

- [1] H. Hashimoto, K. Magatani, and K. Yanashima, "The development of the navigation system for visually impaired persons," in *Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2001, vol. 2, 2001, pp. 1481 – 1483.
- [2] N. Luz, R. Anacleto, C. Martins, A. Almeida, and J. P. Lucas, "Lightweight tourism recommendation," *International Journal of Web Engineering and Technology*, vol. 8, no. 2, pp. 106 – 123, 2013.
- [3] R. Anacleto, N. Luz, A. Almeida, L. Figueiredo, and P. Novais, "Shopping center tracking and recommendation systems," in *Soft Computing Models in Industrial and Environmental Applications, 6th International Conference SOCO 2011*, ser. Advances in Intelligent and Soft Computing. Springer Berlin Heidelberg, 2011, no. 87, pp. 299 – 308.

- [4] J. Murray, "Wearable computers in battle: recent advances in the land warrior system," in *The Fourth International Symposium on Wearable Computers*, 2000, 2000, pp. 169 – 170.
- [5] J. Ramos, R. Anacleto, A. Costa, P. Novais, L. Figueiredo, and A. Almeida, "Orientation system for people with cognitive disabilities," in *Ambient Intelligence - Software and Applications*, ser. Advances in Intelligent and Soft Computing. Springer Berlin Heidelberg, Jan. 2012, no. 153, pp. 43 – 50.
- [6] J. Hightower and G. Borriello, "Location systems for ubiquitous computing," *IEEE Computer*, vol. 34, no. 8, pp. 57 – 66, 2001.
- [7] K. Chintalapudi, A. Padmanabha Iyer, and V. Padmanabhan, "Indoor localization without the pain," in *Proceedings of the sixteenth annual international conference on Mobile computing and networking*, ser. MobiCom '10. New York, USA: ACM, 2010, pp. 173 – 184.
- [8] S. Beauregard and H. Haas, "Pedestrian dead reckoning: A basis for personal positioning," in *Proceedings of the 3rd Workshop on Positioning, Navigation and Communication*, 2006, pp. 27 – 35.
- [9] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments," in *Proceedings of the 10th international conference on Ubiquitous computing*, 2008, pp. 114 – 123.
- [10] V. Renaudin, O. Yalak, P. Tom, and B. Merminod, "Indoor navigation of emergency agents," *European Journal of Navigation*, vol. 5, no. 3, pp. 36 – 45, 2007.
- [11] Y. K. Thong, M. S. Woolfson, J. A. Crowe, B. R. Hayes-Gill, and R. E. Challis, "Dependence of inertial measurements of distance on accelerometer noise," *Measurement Science and Technology*, vol. 13, pp. 1163 – 1172, 2002.
- [12] N. Castaneda and S. Lamy-Perbal, "An improved shoe-mounted inertial navigation system," in *International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 2010, pp. 1 – 6.
- [13] Q. Ladetto, V. Gabaglio, and B. Merminod, "Two different approaches for augmented GPS pedestrian navigation," in *International Symposium on Location Based Services for Cellular Users, Locellus*, 2001.
- [14] A. Hamaguchi, M. Kanbara, and N. Yokoya, "User localization using wearable electromagnetic tracker and orientation sensor," in *10th IEEE International Symposium on Wearable Computers*, 2006, pp. 55 – 58.
- [15] S. Godha, M. G. Petovello, and G. Lachapelle, "Performance analysis of MEMS IMU/HSGPS/magnetic sensor integrated system in urban canyons," in *Proceedings of ION-GNSS Conference*, 2005.
- [16] S. Beauregard, "A helmet-mounted pedestrian dead reckoning system," in *3rd International Forum on Applied Wearable Computing (IFAWC)*, 2006, pp. 1 – 11.
- [17] A. Jimenez, F. Seco, C. Prieto, and J. Guevara, "A comparison of pedestrian dead-reckoning algorithms using a low-cost MEMS IMU," in *IEEE International Symposium on Intelligent Signal Processing*, 2009, pp. 37 – 42.
- [18] D. A. Grejner-Brzezinska, Y. Yi, and C. K. Toth, "Bridging GPS gaps in urban canyons: The benefits of ZUPTs," *Navigation: Journal of the Institute of Navigation*, vol. 48, no. 4, pp. 217 – 226, 2001.
- [19] R. Jirawimut, M. A. Shah, P. Ptasinski, F. Cecelja, and W. Balachandran, "Integrated DGPS and dead reckoning for a pedestrian navigation system in signal blocked environments," in *Proceedings of the 13th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GPS 2000)*, 2000, pp. 1741 – 1747.
- [20] S.-W. Lee and K. Mase, "Activity and location recognition using wearable sensors," *IEEE Pervasive Computing*, vol. 1, no. 3, pp. 24 – 32, 2002.
- [21] O. Bebek, M. Suster, S. Rajgopal, M. Fu, X. Huang, M. Cavusoglu, D. Young, M. Mehregany, A. van den Bogert, and C. Mastrangelo, "Personal navigation via high-resolution gait-corrected inertial measurement units," *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 11, pp. 3018 – 3027, 2010.
- [22] H. M. Schepers, "Ambulatory assessment of human body kinematics and kinetics," PhD Thesis, University of Twente, Netherlands, 2009.
- [23] C. Vaughan, B. Davis, and J. O'connor, *Dynamics of human gait*. Human Kinetics Publishers Campaign, Illinois, 1992.
- [24] P. Kinney, "Zigbee technology: Wireless control that simply works," in *Communications design conference*, vol. 2, 2003.