Person Localization using Sensor Information Fusion

Ricardo Anacleto[1⋆], Lino Figueiredo[1], Ana Almeida[1], and Paulo Novais[2]

[1] GECAD - Knowledge Engineering and Decision Support Research Center,
School of Engineering - Polytechnic of Porto, Porto, Portugal
{rmsao,lbf,amn}@isep.ipp.pt
[2] CCTC - Computer Science and Technology Center, at University of Minho,
Braga, Portugal
pjon@di.uminho.pt

Abstract. Nowadays the incredible grow of mobile devices market led to the need for location-aware applications. However, sometimes person location is difficult to obtain, since most of these devices only have a GPS (Global Positioning System) chip to retrieve location. In order to suppress this limitation and to provide location everywhere (even where a structured environment doesn't exist) a wearable inertial navigation system is proposed, which is a convenient way to track people in situations where other localization systems fail. The system combines pedestrian dead reckoning with GPS, using widely available, low-cost and low-power hardware components. The system innovation is the information fusion and the use of probabilistic methods to learn persons gait behavior to correct, in real-time, the drift errors given by the sensors.

Keywords: Pedestrian Navigation System, Inertial Navigation System, Indoor Location, GPS, Probabilistic Algorithms

1 Introduction

A system that is capable of locate an individual can be explored, among others, to improve life quality since emergency teams (fire-fighters, military forces, policeman's and medics) can respond more precisely if the team members location is known, tourists can have more precise recommendations [2], the elderly can be better monitored [13] and parents can be more relaxed with their children.

The motivation for this project emerged from our previous works, where a recommendation system to support a tourist in his vacations has been developed. However, its major limitation is related to obtain tourist location, which is only

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based on GPS (Global Positioning System) restricting its use to environments where GPS signal is available [1]. Unfortunately, GPS signal is hardly attenuated by obstacles like walls, canyons composed by high buildings or dense forests.

Therefore a system that allows accurate people location, where GPS signal is unavailable, becomes necessary. There are already some proposed systems that retrieve location in indoor environments. However, most of these solutions require a structured environment. One of the first indoor localization systems was based on electromagnetic sensing [12]. After this many approaches have been developed based on smart floor, RFID, Wi-Fi signal strength, ultrasound and many others. Also, computer science companies, like Google [10] and Microsoft [5], are doing some research on indoor localization systems. Therefore, these systems could be a possible solution for indoor environment, but in a dense forest or urban canyons they are very difficult to implement.

To suppress structured environment limitations, an Inertial Navigation Systems (INS) can be developed. An INS is constituted by accelerometers, gyroscopes and other type of sensors based on MEMS (Microelectromechanical systems), which are tiny and lightweight making them ideal to integrate in the person's body. These systems are based on the Pedestrian Dead Reckoning (PDR) technique and the sensors are spread along the person's body to gather acceleration and direction values to estimate the person's walking path. Unfortunately, large deviations of inertial sensors can affect performance, so the INS systems big challenge is to correct the sensors deviations. A module working only with PDR is not able to ensure that the geographical positions are accurate within a few meters.

To reduce these typical errors, Feliz et al. [7] estimates the error in each step of a pedestrian walks to ensure that the small error produced, when speed and position are estimated, will not influence the speed and position estimation for the next step. Castaneda and Lamy-Perbal [4] proposes a fuzzy logic procedure for better foot stance phase detection. Bebek et al. [3] introduce a high-resolution thin flexible ground reaction sensor, which measures zero velocity duration to reset the accumulated errors.

Despite all of these systems can provide localization everywhere there are still lack of location accuracy and some improvements can be made. This paper presents our proposal that includes force sensors and learning algorithms that gathers previous knowledge of the person steps to "self-learn" the user gait behavior, *e.g.*, using GPS when it has very good signal and low error rate to calibrate/learn the INS system. More detailed information about the system architecture will be presented in section 2. Section 3 presents some experimental results and in section 4 are presented some conclusions and the future work.

2 System Architecture

The main claim of our proposal is the capability to retrieve location everywhere, independently of the environment and only based in sensors that are placed in the human body.

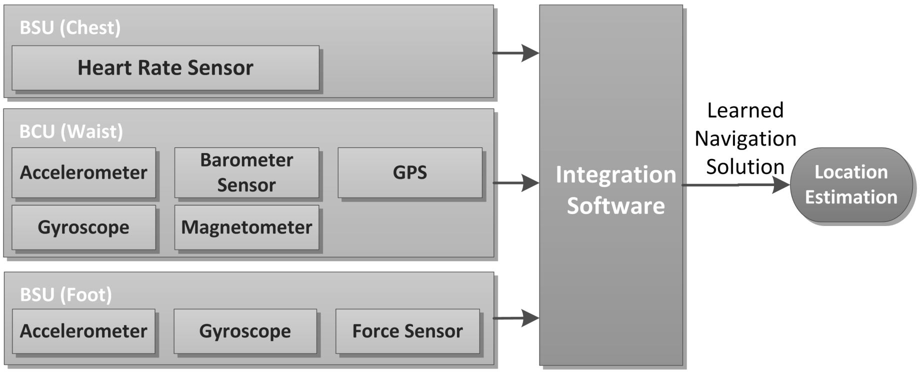

Fig. 1. System Software Architecture.

Our system is constituted by two parts (figure 1), which will be discussed on the next sub-sections:

– Hardware - consists on Body Sensors Units (BSU) placed on the person foot, waist and chest to collect movement's data. These BSU's communicate with a Body Central Unit (BCU) via a wireless network (section 2.1);
– Software - is composed by two parts, the sensor fusion incorporated on the BCU (section 2.1), which integrates the information from sensors and thereby tries to estimate the person location. The other part, implemented on the mobile device (section 2.2), is constituted by the learning algorithms.

Two quantifiable success criteria were defined to this project, the first one is the accuracy that must be between 90% and 95%, and the second one 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.

2.1 Body Sensor Units and Sensor Fusion

Small BSU are placed on the person body to collect information about body movements. In the future we want to integrate these sensors into person's clothes and shoes, to be more imperceptible to the user. This data is sent, through a wireless network based on ZigBee [9], to the BCU that handle the calculations to estimate, in real-time, the person location. The sensors were developed based on the Smart Sensors philosophy, connected to an integrated circuit module to pre-process and codify the collected signal. The BCU module also sends data from the INS system to a mobile device via a Bluetooth connection.

The BSU's are distributed like this, one in the foot that include a force sensor, a gyroscope and accelerometer (figure 2), one in the chest area that include a heart rate sensor, and another in the abdominal/waist area that contains an accelerometer, a gyroscope and a barometer. Force sensors were included since they can improve the detection of the moment when the user touches his feet on

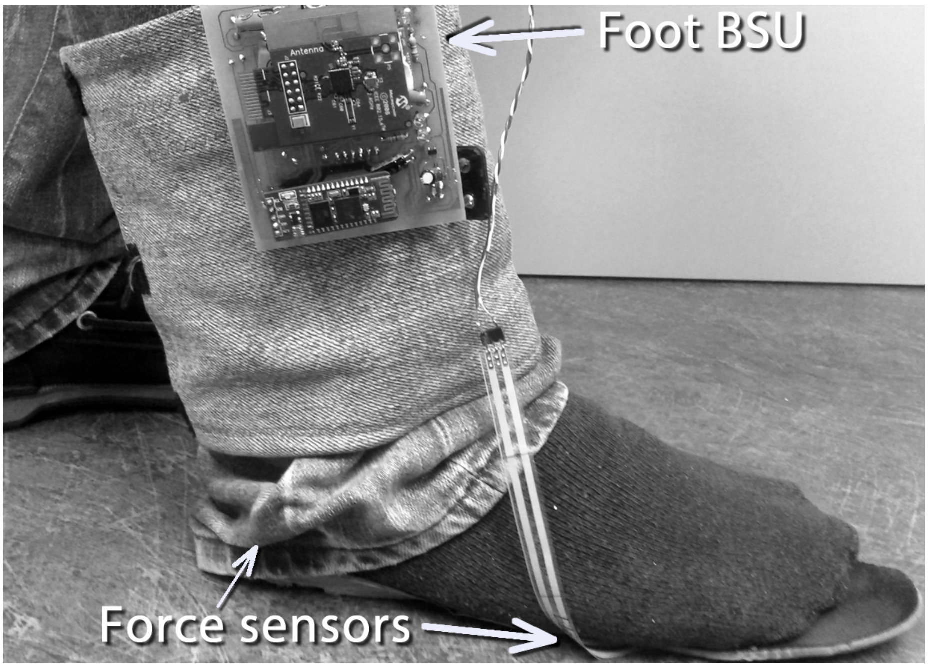

Fig. 2. Foot Body Sensor Unit (BSU)

the ground, as well as, the correspondent contact force, which combined with the accelerometer (used to obtain the step acceleration) provide a more exact step length calculation. The gyroscope is valuable to get the body travel direction, as well as, to transform the acceleration data to the navigation frame. The barometer is used to obtain user elevation. A heart rate sensor is used to know more precisely the user activity (*e.g.*, walking, running, etc.), thus improving the system precision, since when a person is traveling faster the heartbeat is higher than when a person is only standing-up.

In order to have a successful implementation of this wireless network and the corresponding sensors there are some "open problems" that still must be solved. These problems include issues related to deployment, security, calibration, failure detection and power management.

Having several sources of data can be useful to detect more accurately all the person movements, however this integration can be very difficult to implement. From our experience with the INPERLYS project [8], which uses a MEMS accelerometer to estimate the traveled distance and a digital compass for orientation, an INS algorithm working by itself doesn't provide a good location accuracy due to sensors drift errors.

In our approach there are three important software pieces, a preprocessing algorithm on the sensors to remove some noise, a Kalman filter based algorithm to fuse the data from the sensors and a "Learning Algorithm".

Fig. 3. Force sensors location on the foot

Typically the drift is mitigated taking advantage of the Zero Velocity Update (ZUPT) [11], meaning that 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 technique is used by several systems and typically an accelerometer is used to detect when the foot touches the ground. However, our system uses the force sensors to detect it, as well as, the respective contact force. This force information can be also useful to improve the detection of the person activity type (running, walking fast, etc.).

From figure 3 the force sensors position on person foot can be visualized. These positions were chosen since they provide information about when the foot touches the ground (A) and when foot leaves the ground (B). This corresponds to the stance phase of the gait cycle and is during this phase that zero velocity occurs, so the acceleration data isn't considered during this period. These are also the zones where more force is applied on the foot.

2.2 Learning System and Mobile Application

The learning algorithms and a localization module are implemented at the mobile device. In order to reduce errors provided by MEMS, a learning algorithm is being developed to learn the walking/moving behaviors in each type of environment for correcting, in real-time, the data gathered from the sensors.

Walking is a cyclic activity, which represents a cyclic pattern of movement that is repeated over and over, step after step [14] [16]. So, these walking patterns can be extracted in the learning phase and used as a reference model. These patterns are learned, over the 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 the time.

Besides the learning module, another module was developed (for Android OS) to integrate the data from the different sources, and is responsible to retrieve the current user's location estimated by the GPS/INS localization system.

3 Experimental Results

Since the start of this project the research team has been studding and experimenting some implementations, techniques and technologies on pedestrian

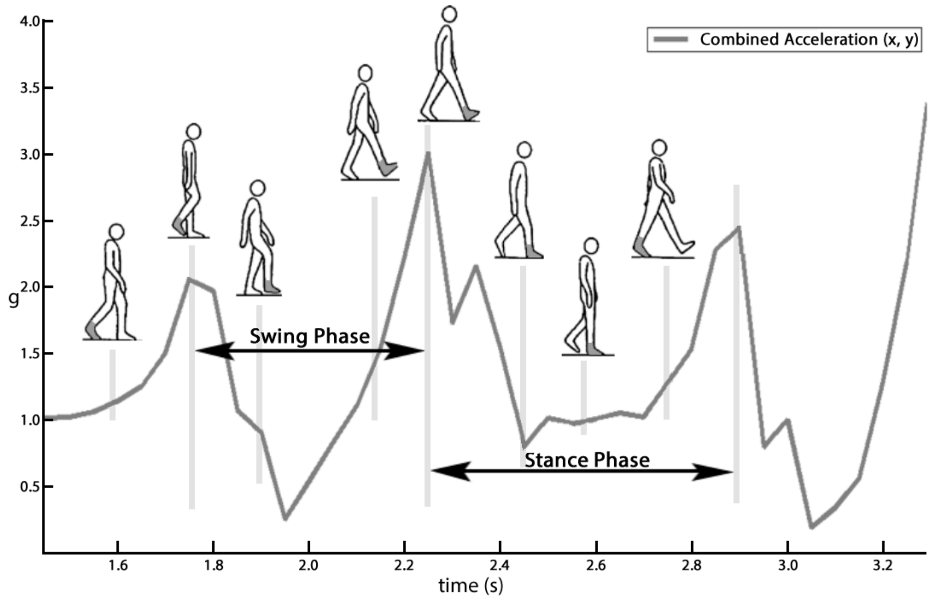

Fig. 4. Foot acceleration during the gait cycle

navigation. With this acquired knowledge and with the encountered problems, we found that an INS solution only based on accelerometers and gyroscopes is not accurate enough.

First of all, the sensors and their positioning. As stated earlier, an INS can bring several problems, especially because of the sensors drift. Also, because of people different sizes, the ideal sensors position to one person can be different to another. This leaves to another challenge, the discovery of an ideal spot for each sensor to work in diverse types of persons. We have found, according to our tests and results, that the ankle is a very good position to put the foot BSU [15], as can be seen on figure 2.

According to the literature the gyroscope bias is the cause of the most of the horizontal errors, so a good practice is to recalibrate the gyroscopes before each experiment. Another sensor that has significant errors is the accelerometer. Figure 4 presents the results of our experiments to determine the acceleration pattern during a gait cycle in a normal walking. Faulkner et al. [6] also have observed that the accelerometer can register large signal peaks. This peaks can introduce some errors to the system if the accelerometer doesn't provide a good acceleration range.

This range can reach $\pm 10g$ when walking and $\pm 13g$ when running or climbing stairs. For best results, accelerometers with at least a $\pm 10g$ range and gyroscopes with a $\pm 900\,^{\circ}/s$ range should be used, which nowadays are a relatively high specifications for MEMS.

A lot of works suggests that the stance phase detection can be tricky, since the accelerometer takes some time in order to obtain that information or due to sensor deviations. In our system force sensors were used to try to overcome this problem, which proved to be a good approach. This sensors are mainly used to distinguish the swing and the stance phase from the gait cycle. It is during the stance phase that zero velocity must occur, since during this phase the foot doesn't move, so no displacement must be considered.

Our tests began with a first approach that uses the Kalman filter in conjunction with a ZUPT module working only with the gyroscope and accelerometer data. These tests were performed on a room involving a total traveled distance of 50 meters. This first approach demonstrated an error of 9.2% on a normal walk path.

After this test the ZUPT module was implemented to only work with the force sensor data. With the use of force sensors the stance phase was better detected, which helped to improve the system errors by 1.3%, this means that the estimated error have reduced to 7.9%.

4 Conclusion

Develop 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 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 it was used a set of small MEMS sensors and the available data was explored to the maximum in order to provide an acceptable level of performance. In the described solution these sensors were spread along the body to detect the person movements in two places, foot and waist.

Since the detection of stance phase using accelerometers and gyroscopes can introduce several errors on INS, our proposal includes force sensors on foot plant to improve the stance detection, and so improve system accuracy. The results from our first experiments, which involved a walk of 50 meters, are very satisfactory, the use of force sensors allowed an average error reduction of 1.3%.

However, a learning algorithm is being developed to improve, even more, the overall system accuracy. This algorithm will learn the person gait cycle when GPS is available or in a learn phase walk, to then in real-time perform corrections in the INS, thus improving INS accuracy.

Another important point of an INS is to inform, in real-time, the user's current location and not only record positions for future walking path analysis. However, sometimes this task is difficult to implement due to the process complexity mainly because of sensor data acquisition delays, communication delays and data processing execution that can take some time. This introduces a significant delay between the real and the processed location (that appears to the user on the mobile device).

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