Improving indoor localisation of firefighters based on inertial measurements

Wilco J. Bonestroo[1], Andre Wassing, Joris Zebel, Henk van Leeuwen

Summary: Knowing firefighters' locations in a burning building would dramatically improve their safety. In this study, an algorithm was developed and tested to enhance the estimation of a person's location, based on inertial measurements combined with measurements of the earth's magnetic field. The developed algorithm is an extension of the zero velocity update technique. Without any enhancements, the accuracy of the estimation is in the order of several meters after measuring for only a few seconds. With enhancements, the accuracy improved to be within five meters after measuring for ten minutes. Our result demonstrated that it is possible to determine in which room and on which floor a person is after ten minutes. Major improvements were observed in the estimation of the sensor's height. The results are promising and the following phases of the project focus on improving the solution and on developing the concept into a practically applicable system.

Keywords: localisation algorithms, inertial measurements, pedestrian dead reckoning, zero velocity update, MEMS IMU technology.

Introduction

There are several ways to determine an object's location. For example, the global positioning system (GPS) is a well-known technology that is used in navigation systems. A major drawback of GPS is that it does not work indoors, because walls and ceilings hinder the radio signals transmitted by satellites. In the current study, we focused on determining the location of a person within a building. The study was performed within the FireBee project [1] that aims to improve firefighters' safety. Firefighters face hazardous situations on a daily basis and sometimes they get injured, become lost, or lose contact with their colleagues. This can lead to dangerous and sometimes even fatal situations. FireBee aims to improve firefighters' communication means and to provide lifesaving information, such as the locations of individual firefighters inside a building. Although our current solution is aimed towards emergency situations, knowledge of the location of an object or a person opens up a world of possibilities and opportunities in domains ranging from logistics to sports and science.

Figure 1 - Inside fire attack

State of the Art

As stated above, there are several technologies to determine the location of a sensor, such as (assisted) GPS, optical systems, radio based systems (time of flight,

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signal strength, angle of arrival), ultrasound systems, laser systems, etc. None of these systems is perfect and each has its typical drawbacks. For example, GPS does not work indoors, ultrasound sensors require clear line of sight, optical sensors have troubles with heavy smoke, and magnetic sensors are disturbed by ferromagnetic materials such as iron. To compensate for such drawbacks, multiple systems can be combined. Besides compensating for the drawbacks, fusion of measurements can also improve the estimations' accuracy. A complete overview of the field of localisation is beyond the scope of this paper. For a review and classification of the field we refer to Muthukrishnan's dissertation [2].

Inertial measurement and dead reckoning

There were several requirements for the solution of the localisation problem. First, the solution should work in situations with heavy smoke with many signal-blocking obstacles in the way, and accordingly no clear line of sight. Furthermore, the solution must not rely on prior knowledge about the infrastructure of the building. Thus, we cannot use the locations of radio beacons. Finally, the solution should be cost-effective.

A common technique that can be used in situations described above is inertial measurement. Recent inertial measurement units (IMUs) are small devices that measure acceleration and rotation using micro-electro-mechanical systems (MEMS) technology. Inertial MEMS sensors are known to suffer from drift and noise, resulting in errors in the output. Another drawback of inertial systems for our problem is that they don't directly measure location. IMUs measure *acceleration* and *rotation*. Thus, when the starting position and the acceleration and rotation up to a certain point in time is known, the position can be calculated. Several other projects tried to estimate the location of a person using one or more inertial sensors with varying results [2,3,4]. There are several approaches to such pedestrian dead reckoning problems. The conventional inertial approach relies on the measured data from the sensor. More advanced methods use additional knowledge, such as the biomechanical model of the person, or use pattern recognition to identify different types of movements. The conventional approach estimates the location by integrating the measured acceleration and rotation values. For example, if the estimated velocity at the previous measurement was 1 m/s and an acceleration of 0.2 m/s^2 is measured for half a second, then the new estimated velocity is 1.1 m/s. If the same technique is applied to the velocity, the position is estimated. With this double integration technique, measurement errors lead to immense errors in the estimated location.

Zero velocity update technique (ZUPT)

A common technique to compensate for the drift and error of IMUs is the zero velocity update (ZUPT) [4,5]. Because the velocity estimation is based on inertial measurements, it is possible that the estimated velocity is not zero, while the sensor is actually not moving. The ZUPT algorithm entails that when a zero velocity is detected, the velocity estimation is forced to be zero. The result is that measurement errors are not blown up, but each time the sensor is in a stationary position, the velocity is corrected to zero. A drawback of ZUPT is the incorrect application of ZUPT or not applying ZUPT while in fact the sensor was stationary. According to the sensor's specification, application of ZUPT results an accuracy of around 2 cm for each step, which means an accuracy of 10 cm for a five second walk [6].

ZUPT extension

ZUPT, as described above, corrects the velocity estimation when the sensor is not moving. However, when the sensor is stationary and the estimated velocity is not zero, there must have been some error in the period between the last and the current ZUPT. Otherwise, the estimated velocity would also have been zero. Therefore, we introduced a velocity correction algorithm that retrospectively corrects all velocities from the last ZUPT to the current ZUPT. In our approach, the error correction is linearly applied to the movement phase. For example, if there are 100 measurements between the last ZUPT and the current one, and the observed error was, for example, 10 units. We update all 100 measurements and apply the error correction with a weight ranging from 0.0 to 1.0. This entails that at the moment the sensor detects a zero velocity, the last estimations are estimated again, resulting in an update for the current position estimation.

A similar technique can be applied to the estimated height. When the sensor is stationary while we are walking on a flat surface, we can assume that the foot is on the floor and not several centimetres above or below the floor. Thus, when a zero velocity is detected and the estimated height is slightly above or below the height during the last ZUPT, a height correction can be applied retrospectively.

Method

Material

We used an Xsens MTw sensor. An MTw is a highly accurate wireless motion tracker that measures acceleration, rotation and the earth's magnetic field, all in three directions. Measurements of an MTw are transmitted to a wireless receiver connected to a computer. In our trials we used a laptop computer to record and store all measurement data. The transmission rate of the sensor was set to 100 Hz.

Figure 2 - MTw sensor

Design

We performed several types of recording trials where participants walked known patterns. The trials included walking on a straight line, walking on a large rectangle, walking in the stair house, and walking for ten minutes throughout the building, starting and ending at exactly the same location. During the trials, measurements were recorded on a laptop, so they could be played back and analysed afterwards.

Based on the recorded trials, all algorithms were run to provide an estimation of the position. These estimated positions were plotted on a visual two-dimensional map, so they could be visually inspected and compared against each other. Our goal was to find an algorithm that could compensate for the measurement errors and give an estimation of the location within the set accuracy bounds.

Results

Without any corrections, there are immense errors in the estimated location. When the participants walked for 6 metres in one direction, we found errors in the estimate of the end position orthogonal to the walking direction (m = 7.54 m, SD = 0.96 m), but also in the walking direction (m = 2.21 m, SD = 1.46 m). After application of ZUPT the accuracy was much better. Orthogonal direction (m = 0.29 m, SD = 0.23 m) and in the walking direction (m = 0.19 m, SD = 0.15 m).

Walking more complex patterns shows similar results. Figure 3 shows two plots of the same measurement data. One plot shows the estimations with corrections and the other without corrections. For detailed descriptions of the measurements we refer to the full research report [7].

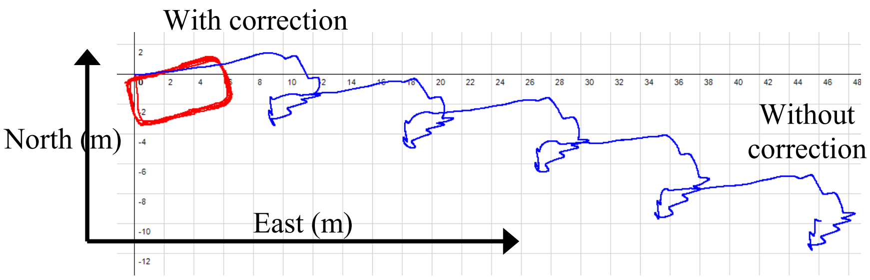

Figure 3 - Two plots of the same measurement data. The deviating plot shows the estimated position without error correction. The rectangular plot show the estimation with ZUPT.

Height

Application of the ZUPT resulted in huge improvements in the estimations in the lateral dimensions. However, there were still large errors for the height. Figure shows the estimated height of a person walking on a flat floor. Figures 4b and 4c show the estimated height of a trial in the stair house. The actual height of the top floor is 15.11 m.

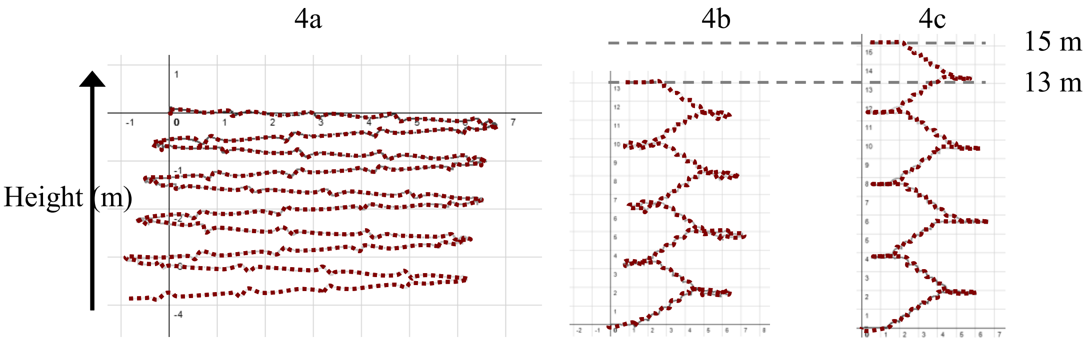

Figure 4a - Height estimation when walking on flat surface with ZUPT. Figure 4b - Height estimation in stair house with ZUPT. Figure 4c - Height estimation in stair house with ZUPT and correction. In all graphs the y-axis represents the height and the x-axis represents the movement towards the east.

Long trial

A longer, ten-minute trial was performed outside the laboratory. Figure 5 shows a plot of the estimations on the map of the building. The observed errors were within 5 m in the lateral directions and within 2 m for the height.

Figure 5 - Long trial in Saxion building

Discussion

We developed an elegant and relatively simple algorithm to enhance the accuracy of the estimated location of a person inside a building, based on inertial measurements. We achieved an accuracy of five meters after a ten-minute walk throughout the building.

Estimations without any corrections are way too inaccurate to be usable. Applying the common ZUPT results in better results, especially in the lateral directions. However, ZUPT still has major errors in the height estimation. Application of both the velocity correction and the height correction resulted in usable results. After ten minutes of walking, we have an accuracy of 5 metres. For example, this accuracy is appropriate to determine in which room and on what floor a person is.

Calculations for the extended ZUPT are relatively light, compared to, for example, the calculations required for the Kalman Filter. So, it can be assumed that the additional algorithms can be calculated in (soft) real time on a microcontroller or another small device that is already running the other filters.

During our study, we observed that the quality of the used sensors was important. Because an Xsens MTw sensor is not really cheap, we hoped that we could also use inferior, low-cost sensors. However, we observed large errors in our estimations when the sensors were not correctly calibrated.

Future work

There are four directions that we want to explore in the following phases of the project. First, we observed some unexplainable errors in the estimated headings that are the result of the Kalman filter. As these errors are relatively large, we need to understand what is happening. Moreover, we have developed some improvements for our algorithms and we have to test whether these improvements actually increase the accuracy.

Second, we want to combine our estimations with other data. Another group in the FireBee project tries to determine the location by using time of flight measurements with radio signals. Results from this group can be fused with and fed into our algorithms to improve the location estimation. A possible direction is the application of particle filters.

Third, the design should be developed into a practical solution. In the current approach, measurements are recorded on a laptop computer and the location estimates are determined using post-processing. However, to be usable in a practical situation, the location estimates should be calculated in real-time on a portable device. That device should be able to communicate with the sensors, to run all the filters, and to communicate the estimated locations to another device. Moreover, we need to test if the circumstances of firefighters cause additional problems with the algorithms. Finally, we want to test the proposed solution with multiple persons, because the recorded trials for the current study were based on two subjects.

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About the authors

Wilco Bonestroo is an instructor and researcher at Saxion University of Applied Sciences. As researcher, he focuses on indoor localisation and sensor fusion algorithms. Wilco has worked as a software engineer at Xsens Technologies.

The work presented in this paper is based on the analysis and algorithms designed by Andre Wassing and Joris Zebel. Andre is a technical computer science student and worked mainly on the ideas and development of the algorithms behind the velocity and the height correction. Joris is a computer science student and focussed on the accuracy of the measurements of the sensors, by analysing bias and noise.

Henk van Leeuwen is lector at the Ambient Intelligence group.

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