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Integrating Low Cost IMU with Building Heading In Indoor Pedestrian Navigation

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Abstract

This paper proposes an integration of 'building heading' information with ZUPT in a Kalman filter, using a shoe mounted IMU approach. This is done to reduce heading drift error, which remains a major problem in a standalone shoe mounted pedestrian navigation system. The standalone system used in this paper consists of only single low cost MEMS IMU that contains 3-axis accelerometers and gyros. Several trials represented by regular and irregular walking trials were undertaken inside typical public buildings. The results were then compared with HSGPS solution and IMU+ZUPT only solution. Based on these trials, an average return position error of below 5 m was consistently achieved for an average time of 24 minutes – at times as long as 40 minutes - using only a low cost MEMS IMU.

Keywords: ZUPT, Kalman Filter, Pedestrian Navigation, MEMS IMU, Heading Drift

1. Introduction

Navigating in indoor environment, particularly inside a building proves to be a complicated navigation problem. An absolute positioning system such as GPS is quite useful and reliable in outdoor environments with a clear view of GPS signals, however using this technology in indoor remains a complicated task. This is because of the fundamental problems of GPS signals, such as low transmission power, which makes it vulnerable to the surrounding environment. As a result, GPS signals will always get attenuated due to reflection and refraction. This is much worse in indoor buildings, where the level of attenuation is significantly higher due to varieties in indoor infrastructures.

Until now, using a High Sensitivity GPS (HSGPS) receiver to produce a continuous reliable position solution in indoor building is very difficult. Although it can be used to detect weak GPS signals, often the signals are not reliable enough to produce good position solutions (Lachapelle 2007). This is partly due to the inability to separate signal errors such as multipath from a good GPS signal. Even if this problem can be overcome, in many situations, there are simply too few GPS satellites in view to be used that have detectable reliable signal and good geometry. A logical approach would be to increase satellite availability. This was investigated by (O'Driscoll et al. 2011) using a combined GPS/GLONASS high sensitivity receiver in urban canyon. However, although the number of detectable satellites did increased, it was found that multipath effect remains a major problem that hinders its advantage.

The question is now whether deviating from using GPS - by using other type of positioning system - is feasible for indoor pedestrian navigation to avoid the problem mentioned before. RFID, WLAN, WIFI and UWB are examples of systems that do not use GPS signals to compute a position solution. RFID uses absolute position information embedded in it to aid navigation system. WLAN/WIFI provides absolute position information through 'fingerprinting' or by using signal strength (Pei et al. 2011). UWB is also using a similar approach of using signal signatures (for example Time Difference of Arrival) to compute position (Kietlinski-Zaleski et al. 2010). All of these however, do require infrastructures, which relates directly to the increase in cost. In some cases – for example during emergency – infrastructures might not be available at all to aid navigation system. This means that resorting to another technology that doesn't rely on external infrastructures is a reasonable option to decrease the cost and eliminate environment disturbances.

A common approach would be to use an Inertial Measurement Unit (IMU), which has the advantage of not relying on external infrastructures. The sensors – normally three accelerometers and three gyroscopes – are small, low power, and inexpensive due to the advances in Micro-electromechanical Sensors (MEMS) technology. Due to its 'dead reckoning' approach, once initialized, the system is totally self-contained. However, the performance of low cost MEMS technology is still relatively low and as a result, their use for positioning applications is relatively limited unless frequent measurement updates from external sensors or technologies are available.

An example of useful frequent measurement updates is Zero velocity UPdaTe (ZUPT) (Skog et al. 2010), which was used successfully in pedestrian navigation to estimate some of MEMS IMU errors. In order to do this, the IMU was 'strapped' on foot/shoe. During walking, the foot has to be briefly stationary (zero velocity condition) in between steps when it is on the ground. These frequent events allow ZUPT to be used to correct the IMU velocity by knowing that velocity should be zero. Furthermore, if the ZUPT measurements are used in Kalman filter, for example in (Foxlin 2005; Godha and Lachapelle 2008; Jiménez et al. 2010), they can not only be used to correct the user's velocity, but also help to restrict correlated position and attitude errors and estimating the sensor bias errors. Therefore, the frequent use of ZUPT measurements consistently bounds many of the errors and as a result, even relatively low cost sensors can provide useful navigation performance.

However, even with the use of frequent ZUPT measurements in Kalman filter, low cost inertial pedestrian navigation systems still suffer from heading drift. This is because of the unobservability of IMU yaw error (assuming that heading drift is primarily caused by accumulation of IMU yaw error). Unobservability is defined as the inability to estimate a state from a given sequence of measurements. In this paper, where only ZUPT is used to aid the low cost IMU, it is then not possible to estimate yaw error using only this measurement. This means that external heading measurements from external sensors are necessary. A common approach is to use magnetometers (Faulkner et al. 2010; Haverinen and Kemppainen 2009; Kemppi et al. 2010; Storms et al. 2010), which is often incorporated with inertial sensors in an IMU, to give the desired heading measurement. However due to significant magnetic disturbances in indoor buildings, this measurement is often unreliable. Instead, it is desirable to use heading measurement updates from other means to properly control heading drift.

As the application is intended for indoor pedestrian navigation, we tried to look for ways that could aid heading drift error when navigating inside buildings. We noticed that a common feature often found in most buildings is that buildings are built in such a way they resemble square or rectangular shape, or a combination of both. Interestingly, rooms, corridors and walls inside these buildings are also often consistent with the outer orientation of the building. Although by no means all buildings are constructed in this way, a good deal of buildings are. For instance, it was reported that 83.2% of high rise buildings in Kuala Lumpur, capital city of Malaysia, are rectangular or square in shape (Ling et al. 2007). As a result, most of the walking in this kind of building is constrained to only follow this feature.

Motivated by this useful information on buildings and how it constrains a walk, this paper presents an approach of using 'building heading' as a measurement update in a Kalman filter. 'Building heading' can be derived automatically from aerial imagery (Abdulrahim et al. 2010), or can also assumed to be known. A new algorithm is developed that integrates the 'building heading' information and ZUPTs in the Kalman filter. We simply assume that most of the walking in indoor buildings is straight, restricted to either one of four possible directions ('4 edges of rectangular'). We argue that when this assumption is invalid, as presented in the result section, the IMU is reliable enough to navigate for a significant period of time without drifting too much.

Note that using a Kalman filter provides us with the advantage of using other reliable measurements as well – if they are available – to further improve the navigation solution. This could be from occasional reliable GPS positions, to WiFi/RFID 'finger printed' positions, or simply a point in a map. This flexibility should provide more integrity and better accuracy to the estimation of system solution, if it can be used reliably to update Kalman filter. However, in our trials, there were no other measurement updates used, except from ZUPTs and 'building heading' algorithm. Note also that there is an advantage of using Inertial Navigation System (INS), as in this paper, against basic Pedestrian Dead Reckoning (PDR) algorithms. Basic PDR assumes that all steps detected are forward walking, thus side-stepping and backward walking lead to false measurements, whereas INS, in contrary, is capable to handle this.

Trials have taken place in a public hospital in Nottingham and several buildings around the University of Nottingham campus, which represents a typical building. Real world measurements were taken from a low cost MEMS IMU that was attached to a shoe. The data were post-processed using a forward Kalman filter only, so that the results can be applied to a real time system in the future. It was then compared with a HSGPS solution and ZUPT only solution. An improvement of almost thirty fold in return position error was achieved, getting an average return position accuracy of below 5 m from an average distance of about 1500 m using the developed approach, against only 154 m using standard ZUPT only approach. Return position accuracy is the accuracy of start and end position, and not a representative accuracy throughout the whole trajectory. This is because there was no ground truth to be used as a reference in the trials. Therefore positions were plotted on Google Earth images for visualization purpose and through this visualization, comparison of position errors were then made. Although there is no absolute sense of quantifying the quality of the solution against Google Earth, it is at least useful to see from the visualization where the positioning has been done and how the heading drift has been reduced.

In summary, this paper presents an approach of integrating 'building heading' information and ZUPT in a Kalman filter, using only low cost MEMS IMU. The idea is to use only IMU for real time navigation, in this paper however, a data logger is used to log the data for post-processing. Using the proposed approach, there is no requirement to have extra sensors to correct heading drift such as magnetometer, camera or optical sensor. There is also no requirement to have a very precise room-level map for navigation. These will be quite convenient for a true low cost pedestrian navigation system in the future. The improvements made in estimating heading error are also analyzed and discussed. True field trials which employ this approach are shown to present the successful implementation of such approach. It is envisaged that a self-contained inertial navigation could be made possible for a longer duration, at least in a typical indoor environment.

2. Inertial Navigation System (INS)

2.1 Equipments

A low cost MEMS IMU from MicroStrain (3DM-GX3-25) was used in the trial. It should be a reasonable representation of a low cost sensor, with typical technical specifications of a low cost IMU grade with a dimension of 44mm x 25 mm x 11mm and weighing only 11.5g. It was strapped on the forefront of a shoe. The accelerometer bias stability is quoted as ±0.01g, and for the 300 degree/s model, the gyro biases are specified as ±0.2degree/s. The particular IMU used has a limit of 1200 degree/s for angular rotation and 18g for acceleration. Although the IMU contains a 3-axis magnetometer as well, only accelerometers and gyros are used for the approach in this paper. Fig. 1 shows the setup. The IMU is shown to be mounted on the foot while the HSGPS receiver and data logger were put inside a backpack. Note that the HSGPS receiver is used only for comparison purpose as presented in result section.

2.2 INS Mechanization

This section briefly describes the INS mechanisation and for more details, please refer to for example (Groves 2008; Shin 2005; Titterton and Weston 2004). The INS mechanisation involves initializing the position and attitude of the INS, before the measurements are numerically integrated to produce attitude and position

Figure 1. Example of system setup

measurements. The initial position for the IMU was estimated from a GPS position (which assumes that navigation would start in a well received GPS signal area). In practice however, a fully GPS-independent system can only be realized by knowing the initial position, for example by standing on a pre-surveyed coordinate. For the initial attitude, a short stationary condition (<10 seconds) is required for coarse alignment. The roll and pitch were calculated by differencing the local gravity vector with the accelerometer measurements, assuming only gravity force is being measured. Initial heading, on the other hand, was initialized manually. It is possible however, to use one-off magnetometer reading, provided that there are no significant magnetic disturbances during this period disturbing the heading measurement. Once it has been initialized, the system will work out its position relative to this initial position.

In order to propagate error states that are being estimated, a standard strapdown error navigation equation was used to update the states vector using phi-angle error model in navigation frame (Farrell and Barth 1999; Shin 2005). The model can be written as follows:

$$\delta\dot{\boldsymbol{r}} = -\boldsymbol{\omega}_{en}^{n} \times \delta\boldsymbol{r}^{n} + \delta\theta \times \boldsymbol{v}^{n} + \delta\boldsymbol{v}^{n} \quad (1)$$

$$\delta\dot{\boldsymbol{v}}^{n} = \boldsymbol{C}_{b}^{n}\delta\boldsymbol{f}^{b} + \boldsymbol{C}_{b}^{n}\boldsymbol{f}^{b} \times \emptyset - (2\boldsymbol{\omega}_{ie}^{n} + \boldsymbol{\omega}_{en}^{n}) \times \delta\boldsymbol{v}^{n} - (2\delta\boldsymbol{\omega}_{ie}^{n} + \delta\boldsymbol{\omega}_{en}^{n}) \times \boldsymbol{v}^{n} + \delta\boldsymbol{g}^{n} \quad (2)$$

$$\dot{\emptyset} = -\boldsymbol{\omega}_{in}^{n} \times \emptyset + \delta\boldsymbol{\omega}_{in}^{n} - \boldsymbol{C}_{b}^{n}\delta\boldsymbol{\omega}_{ib}^{b} \quad (3)$$

where $\delta\boldsymbol{r}, \delta\boldsymbol{v}$, and $\emptyset$ are the vectors of position, velocity and attitude errors respectively, $\times$ is the cross product operator, $\boldsymbol{C}_{b}^{n}$ is the rotation matrix that transform from body frame to local navigation frame, $\boldsymbol{\omega}_{en}^{n}$ is the navigation frame transport rate, $\boldsymbol{\omega}_{ie}^{n}$ is the Earth's rotation, $\delta\boldsymbol{g}^{n}$ is the gravity vector error, $\delta\theta$ is the angle between true frame and navigation frame and $\delta(\cdot)$ represents the error of specific vectors. The position and attitude of the system can then be regularly updated by numerical integration of the IMU output.

2.3 ZUPT Detection using Angular Rate

Correct stance phase detection is essential in a self-contained inertial navigation system that uses ZUPTs. This is because it enables ZUPTs to be used correctly in the Kalman filter for state error estimation. Zero velocity detection based on angular rates was used for this purpose and proved to be fairly robust in detecting stance phase for the trial. Angular rates detection was used mainly because it was shown in (Feliz et al. 2009; Skog et al. 2010) to slightly outperform commonly used acceleration based detection, namely acceleration moving variance detection and acceleration magnitude detection. The improvement was demonstrated in terms of reliability of step detection during different gait velocity. As a result, this method gives a satisfactory result with regards to step misdetection and works fairly reliably at least for the trials described in this paper.

First, a simple moving average filter with a window size of 7 measurements was used to smooth out some of the short term angular rate measurement fluctuations. Then an empirically determined threshold is applied to the magnitude of angular rates to detect a stance phase condition (zero velocity condition). The measurements are then decimated to 20Hz and another integrity check is then applied to ensure ZUPT is detected correctly. This is done by ensuring only two consecutive filtered measurements fall below the set threshold before ZUPT can be declared and used during stance phase. Finally the ZUPT rate is further reduced to 10Hz to reduce Kalman filter computational load before being used in the filter. Fig. 2 shows example of the detected ZUPT events.

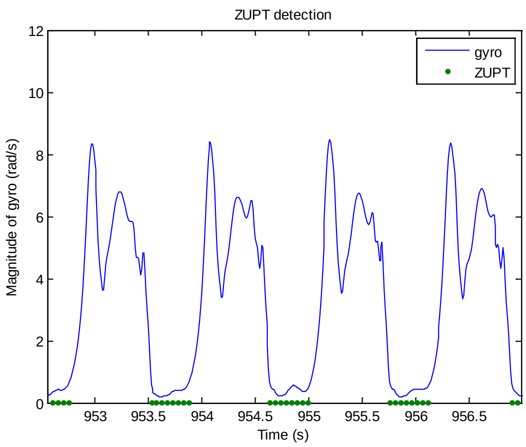

Figure 2. Exampe of ZUPT detection using angular rates detection

3. Kalman Filter (KF)

3.1 Measurement Update using ZUPT

Optimal state estimation using Kalman filter is widely used and extensively reported in literatures such as in (Faulkner et al. 2010; Grewal and Andrews 2008; Hide et al. 2007). Our Kalman filter is used in feedback form, which means that estimated errors from Kalman filter are feedback on every iteration to correct the system, zeroing the Kalman filter states in the process. Due to this, Kalman filter states are kept small and thus maintain the small error assumption of the states. This ensures that the linearized error model assumption in the filter remains to be valid. The error state vector that was used is:

$$\boldsymbol{x} = (\delta\boldsymbol{r}\ \delta\boldsymbol{v}^n\ \delta\boldsymbol{\varepsilon}\ \delta\boldsymbol{g}\ \delta\boldsymbol{a})^T \tag{4}$$

where $\delta\boldsymbol{r}$ is the vector of latitude, longitude and height errors; $\delta\boldsymbol{v}^n$ is the vector of navigation frame velocity errors; $\delta\boldsymbol{\varepsilon}$ is the vector of attitude errors (roll, pitch and yaw); $\delta\boldsymbol{g}$ is the vector of gyro bias errors and $\delta\boldsymbol{a}$ is the vector of accelerometer bias errors. Other IMU errors such as accelerometer and gyro scale factor error, cross-coupling error and gravity dependent error were not modelled in this work. Therefore, the effects these unmodelled errors have towards Kalman filter states were coarsely approximated by increasing accelerometer and gyro noise empirically so that the measurement noise impact is much greater than the unmodelled errors.

In this paper, the knowledge of errors during ZUPT is used as a measurement update in the Kalman filter to better estimate IMU errors. During ZUPT epochs, differences between inertial measurements and the ZUPT condition are entered into the Kalman filter for error estimation. The design matrix used in this paper which uses ZUPT to update Kalman filter is shown below:

$$\boldsymbol{H} = (0_{3x3}\ \ I_{3x3}\ 0_{3x3}\ 0_{3x3}\ 0_{3x3}) \tag{5}$$

with observation $\boldsymbol{z}_k = \delta\boldsymbol{v}^n$ and covariance matrix $\boldsymbol{P}_k = E(\boldsymbol{n}_k\boldsymbol{n}_k^T)$,, where $\delta\boldsymbol{v}^n$is the difference between the INS velocity and zero, $\boldsymbol{n}_k$ is a constant measurement noise and k is the current epoch.

3.2 Measurement Update using Building Heading

In (Abdulrahim et al. 2010), the heading of a building is derived from an aerial imagery map. The ‘produced heading’ therefore, either derived or assumed known, is a single value for a particular building. Due to the assumption that most buildings are in square or rectangular shape or both, there will be then four principle possible directions of walking, thus four possible ‘headings’. These four possible ‘headings’ are actually just a 90 degree offset from each other, making the derivation of ‘building heading’ a simple task.

In order to use ‘building heading’ correctly in the algorithm, a correct heading quadrant has to be chosen (due to four possible ‘building headings’). This is because, only one heading measurement is needed by the algorithm to update Kalman filter. Remember that we have four derived 'building headings', as a result of the assumption on building shape. Therefore, out of these four 'building headings', only one is correct at any instance.

The algorithm starts by running a check on the system, to determine whether a step has been taken or not. The changes in horizontal position (North and East) are used to compute a step length in meters. Knowing that it is possible a step has been taken if the measured step length is more than 0.5 meter, and is almost impossible for a normal user to take a step more than 10 meter in length, an empirically determined step length threshold is used to verify indeed a step has been taken. If it returns true, it goes to a second stage of the algorithm, where the task is to calculate a step heading, as explained below. Otherwise, no update is applied to Kalman filter states.

The second stage of the algorithm involves calculating a step heading. This was calculated at every ZUPT epoch. A step heading is defined as the change in heading measurement at current epoch (*t*), from previous epoch (*t*-1). It is conveniently chosen with the assumption that within this epoch the IMU error remains small. The following equation is used to calculate step heading by utilizing *atan2* function, which is just a variation of *arctan* function to resolve the angle in the right quadrant.

$$\widetilde{\psi_s} = atan2\left(\frac{\Delta E}{\Delta N}\right) \tag{6}$$

where $\widetilde{\psi_s}$ is the measured step heading and ΔE and ΔN are the changes in East and North position over one step. This heading measurement is based only on the change in position caused by a single step, and therefore it consists of not only the true heading plus drift, but also other unmodelled errors from inertial navigation.

After that, the algorithm will proceed to the third stage, where it will determine which one of the four 'building headings' is to be used. Due to equation (6), the calculated step heading is unambiguous, in a sense that it can now be in any of the four heading quadrants of the building. Therefore, if the difference between the calculated step heading with any of the four 'building headings' falls to a certain threshold, that particular 'building heading' will be chosen as the correct heading at that particular time, which represents the correct direction of user's heading.

Using this correct 'building heading', an observation equation ($\boldsymbol{z_k}$) is formed that represents the observed heading drift error in navigation frame,

$$z_k = \delta\psi^n = \psi_B - \widetilde{\psi_s} \tag{7}$$

where ψ_B is the correct 'building heading' and $\widetilde{\psi_s}$is the measured step heading from raw IMU measurement. When pitch angle (θ) is not equal to 90 degree, the heading angle (ψ) can be computed from the elements of Direction Cosine Matrix (DCM) as (Titterton and Weston 2004):

$$\psi = tan^{-1}\left[\frac{DCM_{21}}{DCM_{11}}\right] \tag{8}$$

The design matrix ***(H)*** for heading error observation equation is then constructed using yaw partial equation as (Shin 2005):

$$\boldsymbol{H} = \left[0_{1x3}\ 0_{1x3}\left(\frac{\partial\hat{\psi}}{\partial\phi_N}\ \frac{\partial\hat{\psi}}{\partial\phi_E}\ \frac{\partial\hat{\psi}}{\partial\phi_D}\right)\ 0_{1x3}\ 0_{1x3}\right] \tag{9}$$

with measurement from equation (7). Note that an appropriate measurement noise has to be used to accommodate steps that are not consistent with the building, for example from zigzag walking. Furthermore, we also assume the heading error is the main source that contributes to position drift error.

3.3 The Use of Kalman Filter

Potentially, by using Kalman filter, all type of observations or measurements that are known, in particular during stance phase, can be used to update the Kalman filter. For example, if there are reliable occasional position updates from GPS, the design matrix ***(H)*** can be constructed as:

$$\boldsymbol{H} = \left[\begin{pmatrix} R_N + h & 0 & 0 \\ 0 & (R_E + h)cos\lambda & 0 \\ 0 & 0 & -1 \end{pmatrix} 0_{3x3}\ 0_{3x3}\ 0_{3x3}\ 0_{3x3}\right] \tag{10}$$

with

$$\boldsymbol{z_k} = \delta\boldsymbol{r} \tag{11}$$

where $\delta\boldsymbol{r}$ is the difference between INS and GPS position, $R_N$and R_E are the major and minor radius of the Earth respectively. Due to the nature of Kalman filter which uses every available observation, the proposed system is therefore conveniently ready for future integration with other reliable observations, where possible.

In our Kalman filter configuration, ZUPT was used with a constant empirically determined measurement noise. However, it was demonstrated recently in (Bebek et al. 2010) that the use of a pressure sensor to detect the correct moment of ZUPT for shoe mounted system, produced more accurate detection in the middle of the shoe. This is important for a subsequent accurate position determination. Therefore, it will be a focus of our future work to try to adaptively tune measurement noise for ZUPT measurement. One possible way is to decrease the measurement noise value in the middle of every ZUPT measurements, while keeping it constant at the start and at the end of the measurements.

Similarly, the 'building heading' measurement was also updated to KF with a constant measurement noise. One possible way to improve the estimation process is to investigate the effect of tuning the measurement noise to the algorithm using innovation residual based approach (Hide et al. 2003). However the tuning of the measurement noise must be investigated carefully as it can be extremely volatile if the three Kalman Filter assumptions fail: no time correlation of process noise, no time correlation of measurement errors and no time correlation between process noise and measurement noise (Mohamed and Schwarz 1999).

4. Results

The first trial using proposed algorithm was performed inside a hospital in Nottingham on June 2010. A user equipped with the equipments as described in section 2.1 was asked to walk around inside a hospital. The walking trial was performed for about 40 minutes with an approximate distance of 2400 meters. The user started walking from the outside of the hospital, and walking into the hospital through the main entrance. After walking was done inside the hospital, the user walked out again through the same entrance, back to the same starting position. The reason behind starting and ending at approximately the same position is to ensure we are able to quantify the return position error. This is because ideally, starting and ending at exactly the same location should give us a 'zero' return position error. The HSGPS receiver was only used for comparison purposes to indicate the performance of a high sensitivity receiver in this building.

Fig. 3 shows the output of HSGPS receiver. There were significant jumps in the solutions – at times beyond the hospital's walls – which make it impossible to compare it with the proposed system. In contrary, Fig. 4 shows the output of the IMU, which was updated with ZUPT. Although there are still significant position errors as a result of heading drift, we can start to see the walking trajectory through continuous position solutions from the IMU. Finally Fig. 5 shows the proposed system position solutions. It is obvious that the proposed system solution overcomes the other two approaches of using HSGPS and IMU + ZUPT only solution, based on the difference between these two trajectories. Note that only coarse comparison of the trajectory was made between the three solutions as a result of unavailable ground truth as a reference. However, it does provide a useful insight into the effectiveness of this approach against a standard ZUPT and HSGPS.

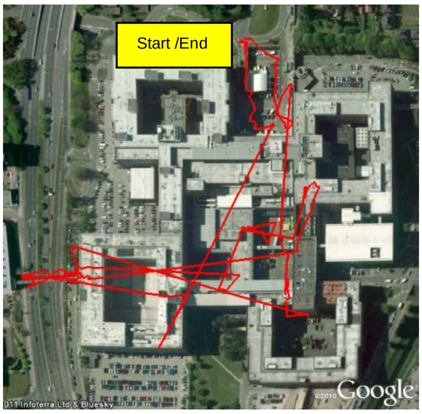

Figure 3: HSGPS solution

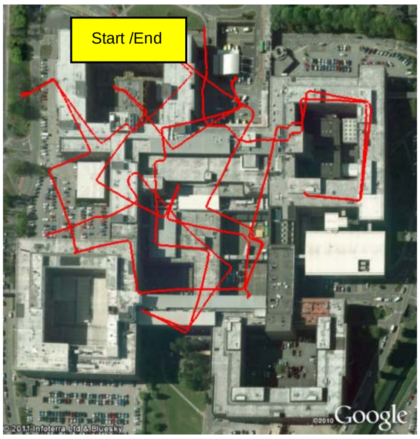

Figure 4: IMU+ ZUPT solution

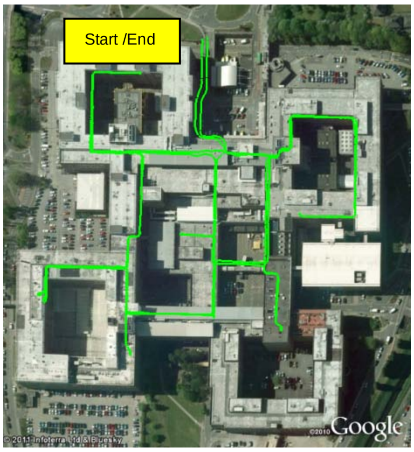

Figure 5: The position output of the proposed system

Table 1: Summary of all walking trials

Trial	Description	Duration (minutes)	Distance (m)	Return Position Error: Heading Aided (m)	Return Position Error: No Heading Aided (m)
1	Straight pathway	15.7	496.8	6.25	270.42
2	Car park	12.7	905.4	3.96	28.63
3	Football pitch	40.3	3000	4.42	34.58
4	Hospital 1	30.4	1973.7	4.23	109.6
5	Hospital 2	21.9	1443.9	7.6	518.24
6	Hospital 3	38.8	2665.3	3.11	204.21
7	Hospital 4	16	918.8	6.2	38.73
8	Campus	14.83	1066	1.19	24.52
AVERAGE		23.79125	1557.46	4.62	153.61625

A few more trials were undertaken and the results are summarized in Table 1. The first trial, as explained before, is tabulated as trial 4 in Table 1. All the trials lasted for a period of at least 10 minutes and above, with a minimum and maximum distance of about 500 m and 3000 m respectively. The time is measured using the timestamp in the IMU output file while the distance is measured using raw IMU position output. For an average of 24 minutes of walking with an average calculated distance of 1500 m, using 'building heading' aided approach gives us an average of below 5 m return position error. In contrast, without using 'building heading' approach, the return position error is well above 150 m.

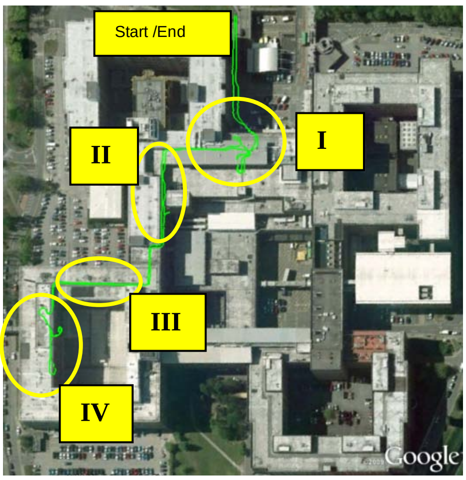

Figure 6: Trial with irregular walking (I,II,III and IV sectors)

In order to examine how robust the algorithm is when the assumption to walk in straight lines in indoor environment does not necessarily hold true, a trial with an irregular walking pattern was attempted for a period of 15 minutes. This was labelled as I, II, III and IV in Fig. 6 where I represents walking and wandering around in a shop; II represents a zigzag walking; III represents backwards walking; and IV represents walking down and up a spiral stair for a few levels. With these irregular walking patterns, the start and end position error still gives an error of only about 1.25 m, approximately 0.1 % of the total walking distance of ~1248 m.

5. Conclusion

This paper presented an approach to restrict heading drift error in low cost inertial pedestrian navigation system. This was performed by using true 'building heading' information in Kalman filter. An algorithm to fuse this information inside Kalman filter is explained. A result of several walking trials was then presented. It was shown to give an average return position error of only 4.62 m in 24 minutes, with an average distance of 1.57 km. It was shown from the trial result that a significant improvement in position can be achieved using only a low cost IMU, without relying on external sensors such as magnetometer or camera to determine heading.

In addition, the use of 'building heading' information provides many advantages to indoor navigation system. It is only needed once for the developed algorithm to form the heading observation equation. Once the system has worked out its heading, repeated requests are not needed anymore. This is very important for a future low cost system with low computing capability, for example one that looks for a real time solution. Furthermore, a precise room level map is not needed, although its inclusion should improve the position accuracy. Therefore, in a Geographical Information System (GIS) database for example, it is possible to associate each building in the database with 'building heading' information to help a user with GIS capability to navigate.

The use of a Kalman filter to integrate 'building heading' information for updating process should also create greater level of integrity and redundancy. For example, occasional reliable positions from GPS can be directly integrated to either update the system with more measurements or as a means to verify the proposed system solution. Theoretically, any possible or relevant measurements from any kind of systems can be integrated with a Kalman filter, thus allowing better estimation of the solution.

Another interesting factor – to use only low cost IMU for navigation – is that it is independent of infrastructures. This permits the use of the system in any kind of environment which has the typical feature discussed in this paper, although the effect of extreme variation in temperature to the IMU performance should be investigated more carefully. This means that the cost of the system is not directly proportional to how big the navigation area is. This is very convenient because a possible true low cost system can be realized from this approach.

It must be mentioned however that the algorithm assumes the user to be walking in either four main headings most of the time in typical indoor building. This is indeed assumed to be valid because in a typical building which has rectangular orientation; most of the corridors, walls and rooms are consistent with building's orientation and as such, restricting users to only walk in either four of these main headings. It is envisaged that extended period of walking in other than main headings will cause suboptimal results – which highlight the need for additional information or sensors – although we have demonstrated in this paper that the algorithm is robust to short periods of movement that doesn't follow these directions.

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