Pedestrian Indoor Navigation Using a Wireless Pocket-IMU and User-augmented Maps

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ABSTRACT

In this paper we describe an infrastructureless indoor navigation system based on wireless inertial measurement units (IMUs). After a short calibration, only one IMU is required, that can be placed in the user's pocket, in contrast to other approaches that require the constant use of a cumbersome foot-mounted IMU. The position accuracy of the system can be improved through map-matching, where the used maps are automatically refined by analyzing user-generated movement patterns.

1. INTRODUCTION

As the importance of location-based services grows, the *accuracy* of location becomes a crucial issue for the success of such services. While outdoor localization via GPS is widely used, indoor localization without the aid of costly infrastructure still remains an area of active research. The practicality of indoor localization is often hindered by insufficient position accuracy or by the need for expensive and cumbersome sensor systems. A number of previous studies have proposed using the principle of *zero updated velocities* (ZUPT). This was first proposed in [6, 3] to cope with accuracy problems arising from the small size of the inertial measurement units (IMUs). Unfortunately, ZUPT requires the IMU to be placed on the foot, which we consider as a major drawback of this technique, since it either conflicts with the aesthetic aspects of everyday life or requires special shoes with a built-in sensor.

To overcome these inconveniences we propose a mobile localization system, based on a small wireless IMU to be placed inside the user's pocket and a handheld device for visualization. Hip-based placement of IMUs was already advocated by Ladetto in [4]. His system needs to be firmly attached to the user's hip and provides less accurate data than a foot-mounted unit. Further, it requires extensive calibration using external components such as a differential global positioning system (D-GPS) with a reference station.

To facilitate such calibration, we, on the other hand, propose an automatic calibration routine based on regular GPS and a second wireless IMU attached to the user's shoe that is only used initially for a short duration. The calibration has to be performed in a region with GPS coverage. This is not a serious restriction - e.g., assume a user entering an airport building inside which indoor localization-based service are to be used.

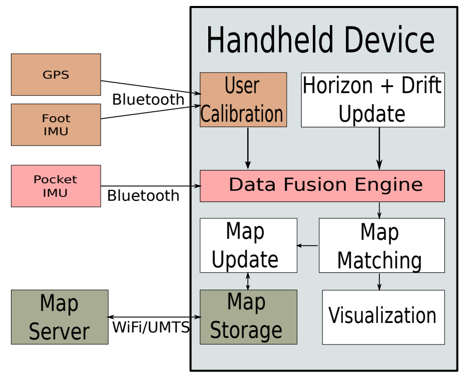

Figure 1: System Architecture

Just before the user enters this building, GPS coverage is available and is used to calibrate the system. The shoe-mounted IMU is only necessary for this first calibration phase when the user starts using the system, and can be detached thereafter.

In order to improve the accuracy of the system, we propose an online update of the IMU's drift parameters, in combination with a *map matching* approach. This is based on a coarse map (e.g., only building contours) that is similar to the one proposed in [1]. We refine this map using the history of movement patterns. The map data can be sporadically transmitted to a central server which fuses the map information with maps gathered from other users and redistributes the refined maps. Using such automatically refined maps allow us to achieve good map matching accuracy without the need for manually providing detailed maps – as proposed in [7] – which are often not available.

2. SYSTEM ARCHITECTURE

Figure 1 shows the systems architecture. The main components of the proposed system are the IMUs, a mobile handheld and a GPS-receiver. The data fusion algorithms run on the handheld device in real-time. The maps used for orientation and filter improvement are stored locally and sporadically transmitted to a map server (if present). Updates from a map server are only necessary only if a new area is to be explored. The mapping information is anonymous and has globally valid tags. Hence, the system need not be bound to a dedicated server and no tight coupling or link monitoring is necessary.

2.1 The Wireless IMUs

The two used IMUs were both custom built using low-cost MEMS sensors. The hip-mounted IMU is of the size of a cigarette box and contains a 3D accelerometer, a 3D magnetic field sensor, three 1D gyrometers and a high-precision pressure and temperature sensor for altitude measurements. The shoe-mounted IMU is smaller than a matchbox and does not contain the magnetic field sensor and the altitude sensor. Sensor data in each IMU is preprocessed on an MSP430 low-power micro-controller and then transmitted via Bluetooth. The entire system is powered via lithium polymer batteries and can be charged using any standard USB port. Because of the low-power mircocontroller and the high efficiency of the switching supplies, the achieved runtimes almost reach 24 hours for low transmission frequencies.

3. SENSOR DATA FUSION

Once the system is started, it first requires a starting position which will be obtained automatically via GPS if the user resides in a region with GPS coverage. If no GPS signal is available, the starting position must be entered interactively, e.g., by indicating a point on the map in the handheld device. After the first localization, the handheld device initiates a wireless synchronisation of the IMUs to ensure that the timestamps generated by all devices match. Once initialized, the IMUs transmit their sensor data to the handheld via Bluetooth. The data fusion and position estimation is entirely performed on the handheld device (which is currently a QT-enabled mobile phone or a laptop). No interaction with any server is required.

3.1 User Calibration Phase

When the system is used for the first time by an user, a calibration phase is necessary. During this phase, the GPS and the foot-mounted IMU are used to obtain the calibration parameters from the user's walking profile (step size, etc.). Once sufficient data is collected (approx. 2 minutes of walking), calibration is performed automatically by determining the users v/f relation. This is similar to the approach described by Ladetto in [4]. If no further calibration is desired, the shoe-mounted IMU may be detached. In contrast to the approaches mentioned in [1, 7] this IMU is not necessary for the navigation process, which we believe greatly enhances the usability of our system.

3.2 Adaptive Extended-Kalman-Filtering

Once the sytem is calibrated, it continuously processes sensor data from the hip-mounted IMU. The orientation of the user is calculated by fusing the data in an Extended-Kalman-Filter (EKF). We dynamically adapt the filtering to the state of the user's movement. When the user is stationary, the gyrometers are not used as filter input. Here, the 3D pose is entirely based on the acceleration data and the magnetic field, and the filter incorporates a bigger resilience to orientation changes. On the other hand, when the user is moving, the impact of the magnetic field is varied according to the fluctuation in the total observed magnetic field. Compared to standard approaches based on fixed and predetermined variances, we obtain a significant gain in robustness against magnetic disturbances, without loosing the drift-correction aspect of magnetic field measurements.

3.3 Online Drift and Horizon Update

A problem arises when the magnetic field is so much deteriorated that no drift correction is possible. This can be the case when the user is in the proximity of large metallic elements or electronic devices e.g. switching supplies. In this case, drift correction based on the magnetic field is no longer possible. Without a foot-mounted IMU continuous calibration using ZUPT [3, 6] is also infeasible. To overcome the problem of increasing altitude errors due to gyrometer drifts, we use an approach similar to the *virtual horizon* that was proposed by Ladetto in [4]. Ladetto used a static calibration phase and a post-processing phase in order to model a virtual horizon function. This was used to determine the static mount point of the IMU relative to the user and to model the induced altitude variation during each step taken. In Ladetto's work, the horizon function was not changed after the initial calibration, resulting in non-negligible errors when the sensor's position shifts. In order to avoid this shortcoming, we developed an online horizon calibration method. Whenever the system detects a resting period of more than 200 milliseconds, the static position of the IMU is calculated, the drift parameters for the gyrometers are updated and the static variation of the magnetic field is determined. During periods of walking, a shift in the IMU's position is also detected via the low frequency variation of the accelerometer values. This variation is fed into the Extended-Kalman-Filter and used to dynamically estimate the gyro-drift. Hence, we obtain a dynamic drift correction close those obtained by ZUPT, however, without the need of a shoe-mounted sensor.

3.4 Step Detection

Step detection is based on both gyometer and acceleration data. The acceleration data is used to determine the step events. Between two step impacts lies a point where the sensor direction exactly indicates the user's propagation direction. The attitude measured at this point is then used for step propagation and position estimation. The step length is determined by inserting the current step frequency into the calibrated v/f relation.

3.5 The Map Matching Unit

Once the heading and step-length are determined we use a adaptive particle filter [2], to determine position updates. We extended this particle filter with a module using the observed itineraries in order to improve the granularity of a given map. The learning process starts as soon as the probability density function for the position of the user – equipped with our proposed system – converges. We assume that the position of the user is known at startup, hence the initial variance in the probability density distribution is low and the particle distribution converges quickly. This leads to a fast start of the learning process.

Figure 2 shows a simulated itinerary inside an office building. The points indicate the center of the particle distributions the circles indicate their variance. The user enters a formerly unvisited room without prior information except for the coarse-grained map. The particle distribution is relatively wide. When the user leaves the room again on the same itinerary the distribution becomes significantly denser indicating a higher position accuracy.

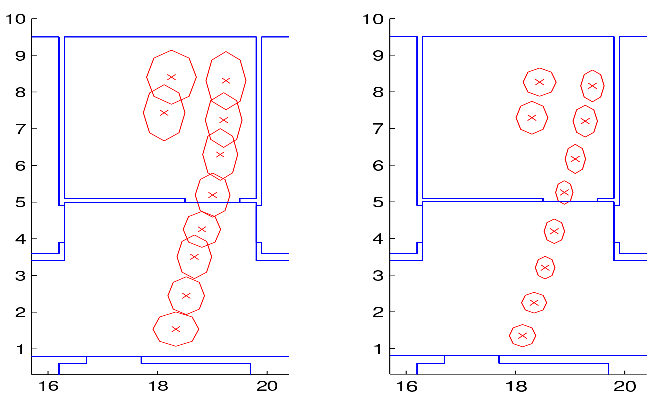

Figure 2: Evolution of the particle distribution through learning. The right figure shows improved position accuracy (i.e., smaller variance)

A similar mechanism for simultaneous mapping and localization (SLAM), solely based on IMU data has recently been proposed in [5]. Our approach differs from this since it relies on a coarse map and uses a less sophisticated filter. But since we can base the individual learning process on far less particles, our algorithm runs in real-time and does not require offline post-processing. The module learns the accessibility of the building based on the evolution of the particle distribution over time and an individual user can immediately profit from a more accurate mapping information.

At larger intervals the refined map is uploaded onto a central server and fused with maps obtained from other users. Thus, with increasing user numbers a fine-grained map of the traveled itineraries is created, which represents all accessible places within region. The resulting distribution can be spread to provide more accurate maps to all users of the system, increasing the position accuracy significantly. This is especially feasible within buildings such as airports, where location-based services also appear to have a significant about of potential.

4. CONCLUDING REMARKS

Our main goal in this paper was to provide a practical and user-friendly indoor navigation solution – (i) with wearable unobtrusive sensors, and (ii) without the necessity of having major infrastructural changes to be imposed on the areas to navigated. We hoped to achieve this goal by using a pocket-placeable IMU as the main sensor. To overcome the drift-induced accuracy problems resulting from this setup, we introduced an automatic drift and horizon correction method. Further, we increased position accuracy using coarse-grained maps that can be easily obtained from conference organizers or building plans. These maps are subsequently enhanced using user-generated detail. Using this approach we hope to obtain sufficient position accuracy for a wide variety of location-based services without relying on cumbersome sensors and attachments. As a part of future work, we plan to evaluate this setup in a variety of building topologies. It would also be interesting to investigate techniques for improved energy efficiency, e.g., by occassionally switching off a part of the system.

5. REFERENCES

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