STRATEGIES FOR THE DEVELOPMENT OF THE NEXT GENERATION OF MOBILE MAPPING SYSTEMS

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ABSTRACT

Mobile Mapping Systems (MMS) refer to an increasing range of moving platforms upon which multiple sensors and measurement systems have been integrated to provide continuous, three-dimensional positioning and orientation of the platform and simultaneously collected spatial data. In order to increase the uptake of MMS across the industry sectors that can most benefit, the limitations of cost and usability facing current generation MMS need to be addressed. This paper proposes that these limitations can be addressed by integrating research developments in the fields of positioning technologies, spatial cognition modelling and human behavioral studies. Whilst these areas of research have previously been undertaken in relative isolation, it is anticipated that their inherent synergies for MMS as presented in this paper will offer some novel perspectives for developing the next generation of MMS.

Specifically, this paper addresses the performance issues associated with the use of the Global Positioning System (GPS) and low-cost positioning and orientation sensors for MMS. It presents algorithms for integrating the on-board positioning and orientation sensors with the view to making them more robust. Additionally, this paper presents a typical approach drawn from current research in human spatial cognition studies that aims to convert measured data into information and ultimately knowledge for the user. Finally, this paper will outline the next phase of this research that aims to fully integrate these independent research themes to develop the next generation of robust, context aware MMS.

1. INTRODUCTION

Mobile Mapping Systems (MMS) refer to an increasing range of moving platforms upon which multiple sensors and measurement systems have been integrated to provide continuous, three-dimensional positioning and orientation of the platform and simultaneously collected spatial data. MMS are currently recognised as an efficient means of spatial data acquisition, and many approaches have been taken to develop MMS that meet the performance requirements of an increasing number of users, and in particular non-specialist or “naïve” users. However, to date, whilst there are a limited number of commercial solutions promoted internationally, or currently in use across a number of industry sectors, their use is restricted to high end applications or for use by specially trained personnel only. There is still no off-the-shelf integrated MMS or solution available. This is directly due to limitations faced in terms of cost, usability and the availability of automatic processing techniques through which data can be converted into information and ultimately knowledge.

It is significant to note that these limitations of current MMS are also affecting the development of a broad range of Location Based Services (LBS). For example, the availability of information that describes the integrity or the quality of the data collected or the information provided, and which is presented in an intuitive manner to a user, has a direct impact on the successful uptake of any LBS or MMS. As such, the distinction between precision LBS (those LBS requiring higher positioning accuracies) and MMS is becoming increasing blurred, particularly with regards to shared problems of usability and knowledge representations.

This research proposes that the limitations of current generation MMS and LBS can be addressed by integrating research developments in the fields of positioning technologies, spatial cognition modelling and human behavioural studies. It focuses on the processes and models that attempt to continuously and accurately track the mobile platform, to automatically extract relevant information from the data sets collected and to communicate this to the user in an understandable, accessible and user-friendly. As such, this paper presents an innovative approach developed to address the performance issues associated with the use of the Global Positioning System (GPS) and low-cost positioning and orientation sensors for MMS. It presents algorithms developed for integrating the on-board sensors with the view to making them more robust, therefore requiring minimal user interaction and complex configurations. This paper also presents an approaches drawn from current human spatial cognition studies that aims to convert measured data into information and ultimately knowledge for the user. Finally, this paper recognises that whilst these areas of research have previously been undertaken in relative isolation, it is their inherent synergies for MMS that offers some novel perspectives for developing the next generation of MMS. A methodology that aims to fully integrate these research areas is outlined in this paper.

2. POSITIONING AND TRACKING TECHNOLOGIES FOR MMS

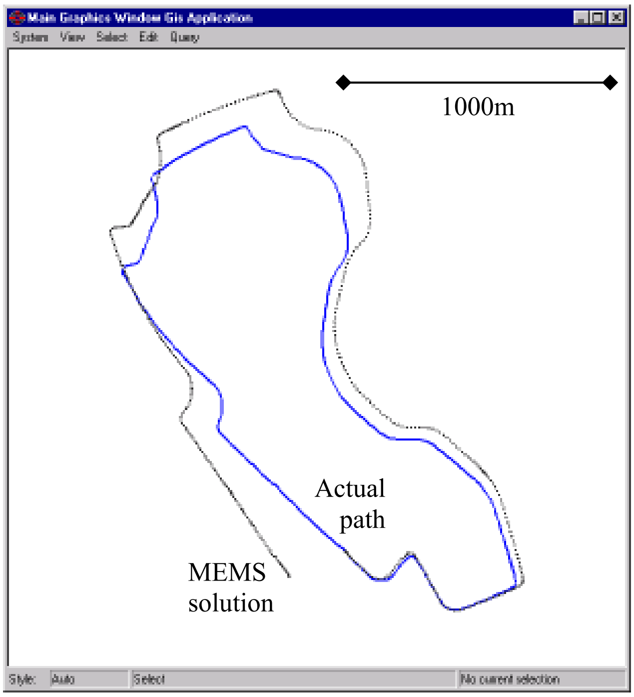

Fig. 1 Accumulation of error using low-cost sensors

Modern MMS typically use the GPS as the primary technology for absolute position determination. Periods over which GPS signals are unavailable are usually bridged using measurements from augmentation sensors such as gyroscopes and accelerometers that integrate measurements of the distance travelled and platform orientation. Unfortunately, these sensors also suffer from their own limitation of drifts over time. The magnitude of these drifts is dependent on the quality of the sensors themselves, with ultra low-cost sensors able to accumulate errors of up to 200m over ten minutes as shown in Figure. 1.
Therefore, whilst the integration of multiple sensors is an effective

approach to providing a robust position solution in current MMS, the practical use of low-cost sensors is still limited. To develop a positioning technology capable of meeting the performance and cost requirements of next generation MMS, this research proposes a fusion of observations from any available positioning technologies (Table 1). The algorithms developed in this research and presented here are based around a rigorous analysis and modelling of the inherent sensor errors integrated within a centralised Kalman filter that is constrained using ‘smart’ modelling techniques.

Positioning Method		Observations	Accuracy
GNSS	GPS	y, x, z	± 6 – 10 m
	DGPS		± 1 – 4 m
Velocity from GNSS		v_y, v_x v_z	~ ± 0,05 m^{-1} ~ ± 0,2 m^{-1}
Cellular Phone Positioning (GSM)	Cell ID	y, x	± 150 m – 35 km
	Solo Matrix		± 50 – 100 m
WiFi Positioning	IMST ipos	y, x, z	± 1 – 3 m
UWB Positioning (TdoA)		y, x, z	± 0.2 – 1 m
RFID Positioning (active landmarks)		y, x, z	± 1 – 20 m
Bluetooth (active landmarks)		y, x, z	± 10 m
Inertial Navigation Systems (INS)	Crossbow IMU700CA-200 Inertial Measurement Unit	a_x, a_y, a_z φ, ψ, θ	< ± 8.5 mG < ± 0.03 °/sec
	Cloud Cap Crista Inertial Measurement Unit (IMU)	a_x, a_y, a_z φ, ψ, θ	> ± 0.3 mG > ± 0.009 °/sec
Dead Reckoning	PointResearch DRM-III Dead Reckoning Module	y, x z φ	± 20 – 50 m per 1 km ± 3 m ± 1°
Heading	Honeywell Digital Compass Module HMR 3000	φ	± 0.5°
Acceleration	Crossbow Accelerometer CXTD02	$a_{tan}, a_{\mathrm{rad}}, a_z$	> ± 0.03 ms^{-2}
Barometer	Vaisala Pressure sensor PTB220A	z	± 1-3 m

Table 1 Positioning technologies with their corresponding observables and accuracies (Duffett-Smith and Craig 2004; Imst 2004; Kong et al. 2004; Chon et al. 2004; Crossbow 2004a; Cloud Cap Technology 2004; PointResearch 2004; Honeywell 2004; Crossbow 2004b; Vaisala 2004) where y, x, z are the 3-D coordinates of the current position, v_y, v_x, v_z are the 3-D velocities, a_x, a_y, a_z are the 3-D accelerations, a_{tan} is the tangential acceleration and a_{rad} is the radial acceleration in the ground plane xy, φ is the direction of motion (heading) in the ground plane xy, ψ is the pitch and θ is the roll.

2.1 An Integrated Approach to Position Determination for Next Generation MMS

To achieve a robust positioning solution using all available measurements, the statistical process of Kalman filtering has been adapted for use in this research. For MMS, one of the most valuable aspects of the Kalman filter is its ability to incorporate within the solution, parameters that account for the errors inherent in the augmentation sensors.
The fundamental process employed in Kalman filtering can be summarised as:

(i) selecting a set of parameters that will approximate the location and dynamics of the moving platform;
(ii) adopting a dynamic model that can be used to predict the movement of the platform between epochs;

(iii) employing a least squares estimating technique to integrate the measurements taken at each epoch with the predicted state of the platform.

The integration methodology consists of a state vector of unknown quantities to be solved. Most commonly, the state vector contains parameters to represent (in 3 dimensions) the coordinates, velocity and acceleration of the platform.

$$x_i^{\text{state}} = \begin{bmatrix} X_i & Y_i & Z_i & \dot{X}_i & \dot{Y}_i & \dot{Z}_i & \ddot{X}_i & \ddot{Y}_i & \ddot{X}_i \end{bmatrix}^T \tag{1}$$

The values of the state vector predicted for any epoch will depend upon the parameters chosen to represent the platform movement and the dynamic model adopted to represent the movement from one epoch to the next. A simple dynamic model that has proven to be successful in route mapping applications is one where it is assumed that;

- the platform moves from epoch x_{i-1} at epoch (i-1) to x_i at epoch (i) with an initial velocity $\dot{x}$ and a constant acceleration $\ddot{x}$.
- the uncertainty in the dynamic model between epoch (i-1) and epoch (i), i.e., the "jerk" is a random variable with zero mean and variance σ^2.

The dynamic model is represented as;

$$\begin{aligned} x_i &= x_{i-1}^t + \dot{x}_{i-1}^t \delta t + \ddot{x}_{i-1}^t \frac{\delta t^2}{2} + \dddot{x}_{i-1} \frac{\delta t^3}{6} \\ \dot{x}_i &= \dot{x}_{i-1} + \ddot{x}_{i-1} \delta t + \dddot{x}_{i-1} \frac{\delta t^2}{2} \\ \ddot{x}_i &= \ddot{x}_{i-1} + \dddot{x}_{i-1} \delta t \end{aligned} \tag{2}$$

The process is started by making an appropriate optimal estimate of the state vector at an initial epoch. If the vehicle starts from rest, the coordinates are set at the values given by the GPS receiver while the velocities, accelerations and jerk are set at zero. The variance of this initial optimal state vector can be assumed to be diagonal and appropriate values adopted.

Thereafter, at each epoch the following process is repeated:

1. compute an estimate of the (predicted) state vector and its associated variance matrix from the optimal estimate of the state vector of the previous epoch.
2. form the observation equations by combining the predicted state vector, the GPS measurements for the coordinates and the zero values assumed for the jerk, and
3. compute the least squares estimate of the state vector and associated variance matrix.

Theoretically, the simple dynamic and stochastic models associated with the Kalman filter are easily applied and are certainly appropriate for kinematic mapping when the path is straight and conducted at constant acceleration. For practical rapid mapping applications however, the sinuous paths and constant changes in acceleration encountered challenge the operation of these models. As such, the performance of the filter for high dynamic applications is fundamentally dependent on the appropriateness of the dynamic model selected and the stochastic model used for the jerk. It is this factor that often requires expertise in users of MMS. Two 'smart' approaches to improving the robustness of the Kalman filter solution have been developed and implemented in this research.

2.1.1 Smart Stochastic Modelling

Figure 2 illustrates the response of the standard Kalman filter solution obtained from measurements taken while the MMS vehicle performed a sharp turn of approximately 90 degrees. The simple polynomial function (equation 2) used as the dynamic model is inappropriate for modelling this type of movement and the Kalman filter is incapable of resolving the actual trajectory of the vehicle. By manipulating the stochastic model or variance of the jerk to increase or decrease the reliance on the dynamic model eliminates this effect and maintains an accurate trajectory of the vehicle (Fig. 3).

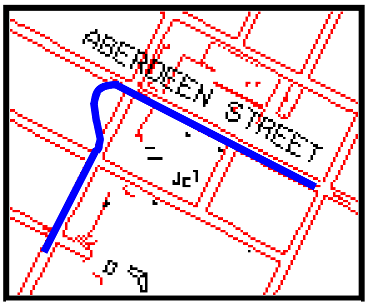

Fig. 2 Typical Kalman filter solution

This technique of smart stochastic modeling (SSM) is implemented when the system output indicates that the motion of the vehicle has deviated sharply from the predicted solution. The predicted measurement residual is tested to determine whether it is an outlier. If it is not flagged as an outlier, the variance of the process noise on the dynamic model is reduced. The filter then weights the observations in preference to the dynamic model, forcing the filter to instantly react to the observations, thereby maintaining the vehicle trajectory.

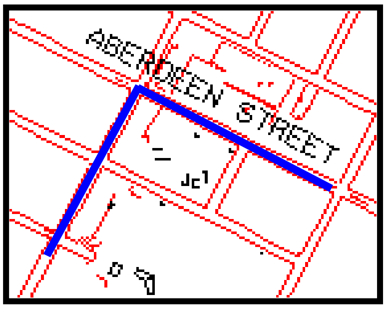

Fig. 3 Smart stochastic modelling

2.1.2 Intelligent Navigation

The integration of the observations of positioning sensors in combination with map matching performed using a Kalman filter approach is referred to as “Intelligent Navigation” (IN).

The IN algorithm developed here is modelled on the simple rules of navigation that humans use on a day-to-day basis, and in doing so incorporates both geometric and topological map matching techniques. This algorithm has several advantages that are:

- It consists of a simple, yet effective set of four rules (closest road, bearing matching, access only and distance in direction).
- It relies on the short term precision of the navigation sensors.
- It assumes that the vehicle is ‘following’ the road network.

The closest road rule of IN makes the assumption that the vehicle is travelling along a road (which is typically the case). This constraint can be included in the location solution, thus improving the accuracy of the computed position of the vehicle. This algorithm is most effective when the nearest road is in fact the road being travelled. However, when approaching intersections or when two roads are close to each other, the nearest road may not be the road being travelled. In such cases, constraining the solution to fall on the nearest road actually downgrades the calculated position. To avoid such errors, the bearing matching rule is required. This rule requires that the nearest road to which the vehicle's position is corrected must have a bearing similar to the measured direction of travel. This corrects the problem previously described. The threshold of similarity between the vehicle's bearing and the bearing of the surrounding roads may be adjusted to suit the accuracy of the navigation sensors. However, the larger the threshold, the more likely it becomes that roads will be incorrectly matched as having the same bearing as that of the vehicle. The access only rule is designed to identify and prevent this error from occurring. By logging previously travelled roads, the navigation system can prevent the vehicle from being located on a road that it could not possibly be on. The fourth rule, i.e., the distance in direction rule, reduces the accumulation of distance error by calculating the distance travelled by the vehicle in the direction of the road rather than the direction measured by the heading sensor. This is particularly important when heading sensors of low accuracy are employed.

Incorporating IN into the Kalman filter requires the development of observation equations from the IN rules. The IN observation equations are derived from the IN estimate of the vehicle's 'corrected' position (which lies on a road segment) and an estimate of the vehicle's heading (i.e., the heading of the road segment at the IN 'corrected' position). This procedure also allows for additional parameters to be estimated by the filter such as the offset from the centreline which is described by the Euclidean distance of the vehicle from the centreline. The process for including IN information and the updated parameters for the state of the Kalamn filter is shown in Fig. 4. Using data from GPS and Dead Reckoning (DR) sensors (eg. gyroscope and odometer), the position and attitude of the vehicle are estimated. This information provides input for the IN algorithms. The results from IN are then combined with the GPS/DR measurements and filtered to provide an optimal solution using all available information. There is only one Kalman filter that has to be run twice where the first run provides the input for the IN algorithms and secund run computes the optimal state of the mobile platform using all available measurements (i.e., GPS, DR and IN). Further details about the algorithm can be found in Scott-Young (2004) as well as Kealy and Scott-Young (2002).

To test the effectiveness of these algorithms, the circuit shown in Fig. 1 was navigated using an integrated positioning system comprising a dual frequency GPS receiver, operating in a real time kinematic (RTK) mode and a low cost inertial navigation sensor (INS) for augmentation. The results from the Kalman filter were compared epoch by epoch to the 'true' position of the vehicle as measured by the differential GPS positions. Fig. 5 shows the error percentages obtained. The integrated positioning system is only able to deliver sub-metre positioning approximately 70% of the time as compared to 95% of the time with SSM and IN.

In Fig. 6, over a duration of five minutes when no GPS positions were available, the integrated positioning system with SSM and IN was able to navigate with approximately 90% of the errors within 1m. This is directly a result of the integration algorithms being able to model the errors in the INS given the added constraints of IN and SSM.

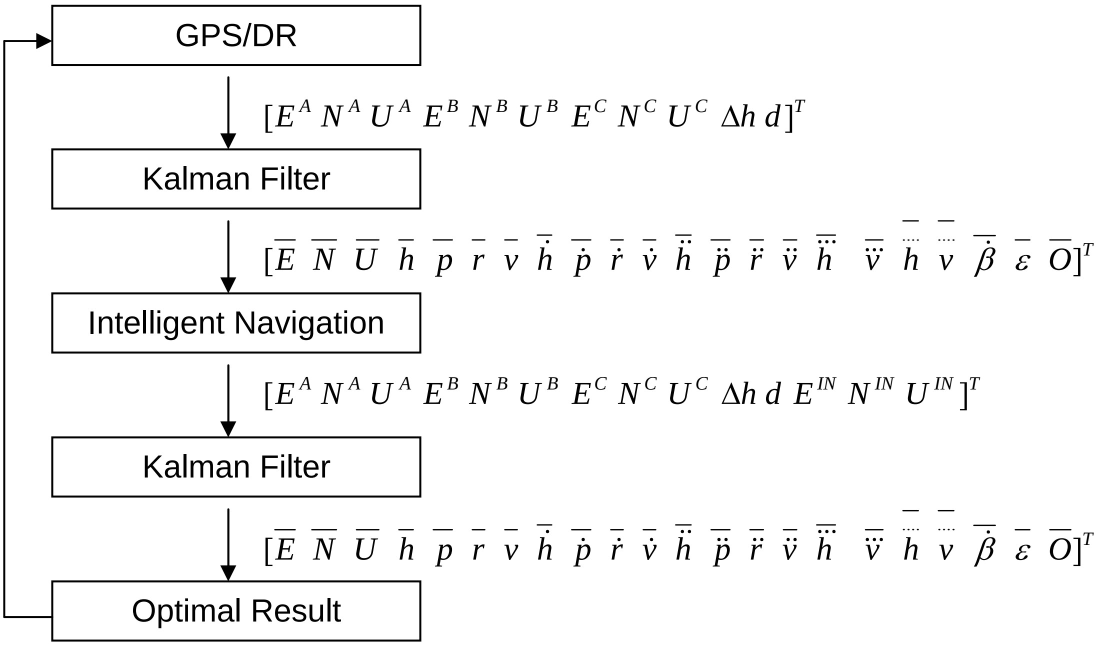

Fig. 4 Kalman filter process with Intelligent Navigation (after Scott-Young 2004) where E^A, E^B, E^C are the Eastings of the three GPS antennas A, B, and C in the platform reference frame, N^A, N^B, N^C are the Northings, U^A, U^B, U^C are the Up coordinates respectively, Δh is the measured change in heading, d is the measured travelled distance, $\bar{E}$ is the estimated Easting coordinate, $\bar{N}$ is the Northing coordinate, $\bar{U}$ is the Up coordinate, $\bar{h}$ is the heading, $\bar{p}$ is the pitch, $\bar{r}$ is the roll, $\bar{v}$ is the velocity, $\bar{\dot{h}}$ is the change in heading, $\bar{\dot{p}}$ is the change in pitch, $\bar{\dot{r}}$ is the change in roll, $\bar{\dot{v}}$ is the change in velocity or acceleration, $\bar{\ddot{h}}$ is the change in $\bar{\dot{h}}$, $\bar{\ddot{p}}$ is the change in $\bar{\dot{p}}$, $\bar{\ddot{r}}$ is the change in $\bar{\dot{r}}$, $\bar{\ddot{v}}$ is the change in acceleration or jerk, $\bar{\dddot{h}}$ is the change in $\bar{\ddot{h}}$, $\bar{\dddot{v}}$ is the change in jerk, $\bar{\ddddot{h}}$ is the change in $\bar{\dddot{h}}$, $\bar{\ddddot{v}}$ is the change in $\bar{\dddot{v}}$, $\bar{\dot{\beta}}$ is the gyro drift rate error, $\bar{\varepsilon}$ is the odometer scale factor error, $\bar{O}$ is the Euclidean distance from the road centreline, E^{IN} is the Easting coordinate as measured from the road database, N^{IN} is the Northing coordinate, U^{IN} is the Up coordinate respectively.

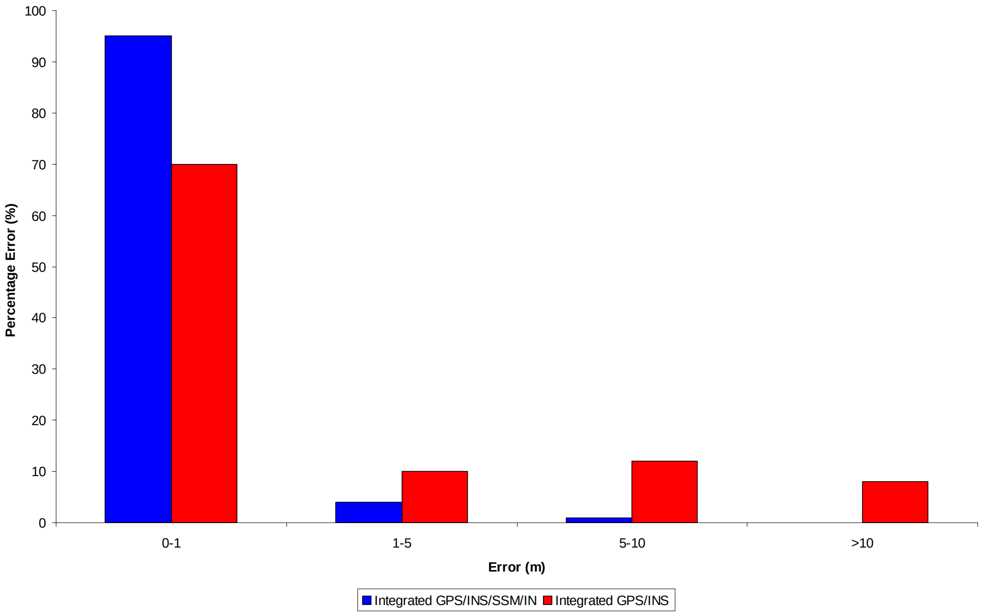

Fig. 5 Comparison of Kalman filter solution for integrated GPS/INS/SSM/IN and Integrated GPS/INS

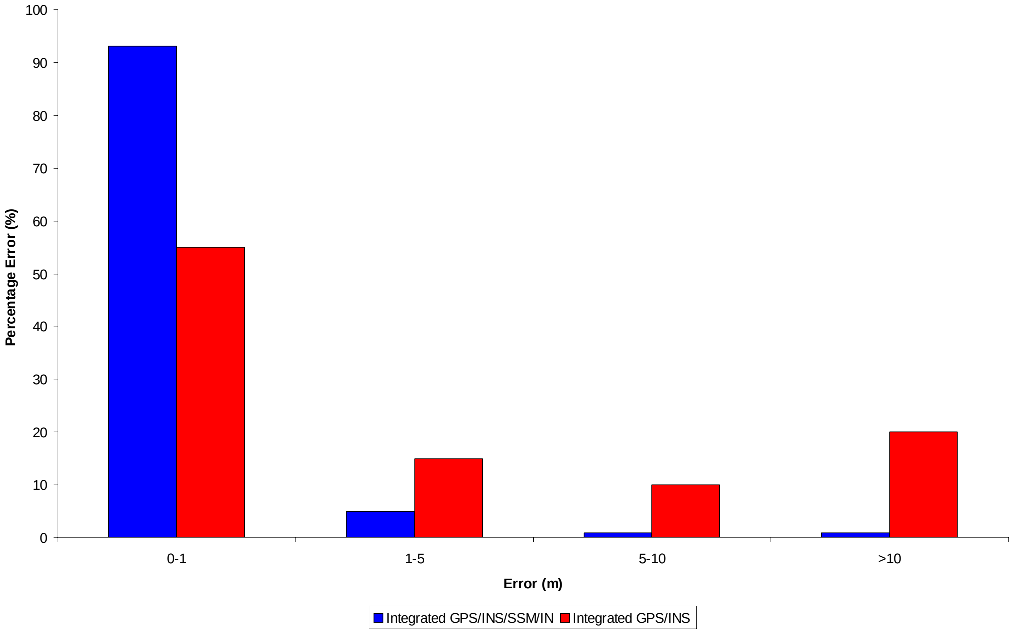

Fig. 6 Comparison of Kalman filter solution for integrated GPS/INS/SSM/IN and Integrated GPS/INS over a period of satellite outage

3. TRANSFORMING POSITION TO KNOWLEDGE IN MMS

The typical output from current MMS is presented as coordinate values and/or raw measurement data collected by the on-board sensors. Conversely, the queries of users of MMS, both expert and non-specialist users, is not for this measured data but for derived information that can be used to support some decision making process. For example, whilst the algorithms presented in Section 2 will enable the computation of an accurate, continuous and reliable position (communicated as a pair of coordinates in some reference system and its variance/covariance matrix), a user may be more interested in a contextualized position (communicated as a street location or some identifiable point/feature of interest). Almost all MMS users currently have to themselves undertake the task of extracting of inferring the information they require from the vast amounts of data collected.

The mechanisms for converting measured data into information and subsequently knowledge is a broad and complex subject of research. In the context of MMS, this research addresses the problem of contextualising coordinate data into more meaningful information. Specifically, it proposes to undertake an analysis of the data collected by on-board sensors and the determination of appropriate mechanisms for communication to the user, i.e., cognitively adequate ways. A case study example undertaken to illustrate this approach is presented here.

3.1 Automatic Generation of a Location Based Travel Diary

In this study a diary metaphor was used to illustrate the goal of mining the tracking data, i.e., finding cognitively relevant patterns in it. It was used to investigate approaches to automatically generating a travel diary from semi-continuous tracking data provided by an example MMS (Andrae 2005; Andrae and Winter 2005). A user tracking herself with GPS continuously over a period of time collected the data used in this study. She simultaneously manually recorded a diary as control data. This data was subsequently analysed to enable the user to pose queries to the system such as: “Where was I at <time>?” or “On which day was I at <location>?”, or more subtle queries.

The key to this analysis involves observing breaks in the travel pattern to separate periods of staying from periods of moving. The algorithms implemented were originally proposed by Hariharan and Toyama (2004). However, in this research the experiments demonstrated that observing a break in a travel pattern is a complex process. The concept of what is a break is imprecise: it is a matter of spatial scale and temporal scale. Additionally, as discussed previously, position solutions are subject to error. For example, when leaving a building and relying primarily on GPS, the MMS needs an initialization phase. The first positioning results in an initialization phase are relatively erroneous (Fig. 7). That means a clustering algorithm searching for stops at the same location over longer periods can easily fail here, although a stop is a prototypical case of a break. In this research, balancing between generous threshold sizes and limiting false positives, the user could identify correctly only 60% of her stops.

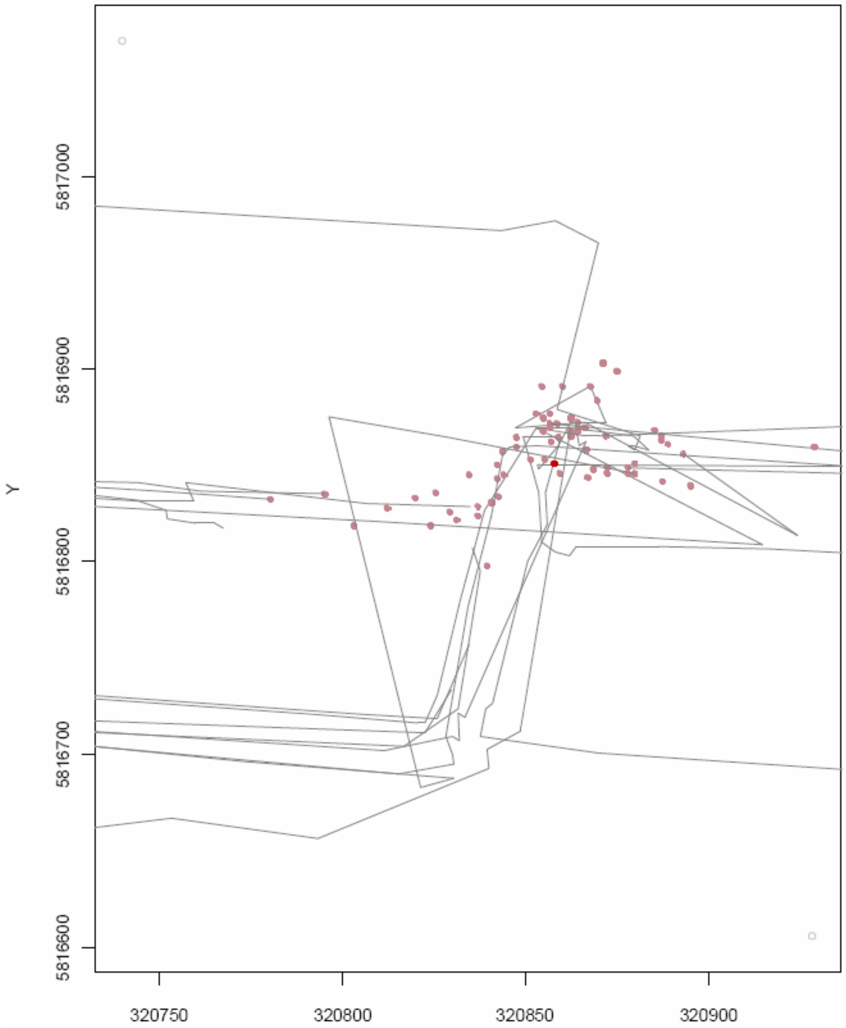

Fig. 7 A detail of a tracking data set in the neighbourhood of the subject's home: note the positioning outliers that occur after leaving the building

A sensible coupling between positioning and analysis could improve this result by focusing the attention of the sensing process to discontinuities in the travel pattern. Some approaches include filtering out unreliable positioning results, increasing the number of observations at spatial or temporal discontinuities, or introducing a knowledge base of events in travel patterns. The latter idea addresses the semantic problem as well as the accuracy problem by defining different resolutions and filter methods for different types of breaks. For example, a "break at home" belongs to the type of extended indoor breaks (other types exist), and this type has large temporal granularity, large spatial granularity (if the person is tracked indoor), and at least two switches of positioning systems (entering and leaving the building). Other distinctions can be made to refine from "extended indoor break": a "break at home" is where persons spend usually the night. It may require entering and leaving through the same entrance point, in contrast to, for example, entering malls or underground stations, which, if considered as a break, have trajectory characteristics.

Analogous to the human visual sense that adapts to different light temperatures without any cognitive effort - white surfaces appear to be white in daylight and in candlelight - similar flexibility in the choice of rule sets have to be realized in the travel sensing-mining process. For example, a switch between GPS and an indoor positioning system indicates that a person has entered a building. The MMS should then switch to rules of smaller spatial and temporal granularity for detecting stops and activities than those applied outdoors. In that way, a "break at home" becomes a complex break aggregated from indoor activities and breaks.

4. A RESEARCH METHODOLOGY TO DEVELOPING THE NEXT GENERATION OF MMS

The previous sections demonstrate that current research is actively developing solutions to the problems facing current generation MMS. However these research initiatives separate the levels of measuring, analyzing and communicating location information. To make significant progress towards developing the next generation of MMS, this research proposes a seamless integration of these levels. It proposes to develop a framework of interlinked procedures and models, and the intelligence to control them, to realize location understanding for intelligent location communication. The components of the framework to be integrated are;

1. A real-time solution for computing positional information in a seamless manner, from a variety of sensor types, in both outdoor and indoor environments.
2. A model of client location for a given position relevant to client needs.
3. A technique for translating the accuracy of the positional data gained in (1) into alternative expressions of location quality.
4. An intelligent model to communicate location to clients in a mobile environment using multi-media techniques that extend beyond the traditional map approach.
5. Active and passive control mechanisms that link (1)-(4). These links consist of procedural knowledge that either triggers actions or limits actions.

The integrated framework will be evaluated within a central demonstrator based around You-Are-Here (YAH) maps. YAH maps are used to relate a user's position with their location contextualized within an environment. For example, emergency plans are commonly used today to convey information on the shortest way out of the building in case of an evacuation. YAH maps pose interesting research questions in terms of how people use them, where to place them, how to design them, or how to assess their understandability. It is an excellent application of how positional data needs to be converted into information and knowledge in order to improve its relevance to a user.

5. CONCLUSIONS

To address the problem of high costs associated with current generation MMS, this research proposes the integration of traditional and emerging positioning technologies with robust integration approaches that will allow for the use of low cost sensors with no compromise in positioning performance.

More significantly, to address the problem of usability associated with current generation MMS, this paper also proposes the integration of research outcomes in the field of human spatial cognition. This integration will extend the quantitative concept of position to user information of location through an active and interlinked hierarchy of sensing and analysis processes.

The paper shows already the viability, directions and benefits of an integrated location analysis. Further research proposed in this paper is directed towards seamless and ubiquitous positioning, towards contextualized concepts of location, and towards an integrated hierarchy of sensing, analyzing, and mining positioning data.

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BIOGRAPHICAL NOTES

Dr. Allison Kealy is Lecturer at the Department of Geomatics of the Melbourne University, Australia. She holds a PhD from the University of Newcastle upon Tyne, UK (1996) specialising in the areas of Kalman filtering, integrated positioning systems and quality control.

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