PERFORMANCE ASSESSMENT OF A MULTU-SENSOR PERSONAL NAVIGATOR SUPPORTED BY AN ADAPTIVE KNOWLEDGE BASED SYSTEM

D. A. Grejner-Brzezinska [a], C. K. Toth [b], S. Moafipoor [a]

[a] Satellite Positioning and Inertial Navigation (SPIN) Laboratory, The Ohio State University, USA - (dbrzezinska, moafipoor.2)@osu.edu
[b] Center for Mapping, The Ohio State University, USA - toth@cfm.ohio-state.edu

Commission I, ICWG V/I

KEY WORDS: Navigation, Multisensor Systems, Knowledge Base, Neural Network, Fuzzy Logic.

ABSTRACT:

The prototype of a personal navigator to support navigation and tracking of military and rescue ground personnel has been developed at The Ohio State University Satellite Positioning and Inertial Navigation (SPIN) Laboratory. This paper provides a review of the navigation techniques suitable for personal navigation and follows with design, implementation and performance assessment of the system prototype, with a special emphasis on the dead-reckoning (DR) navigation supported by the human locomotion model. An adaptive knowledge system (KBS) based on Artificial Neural Networks (ANN) and Fuzzy Logic (FL) has been implemented to support this functionality. The KBS is trained a priori using sensory data collected by various operators in various environments during the GPS signal reception, and is used to support navigation under GPS-denied conditions. The primary components of the human locomotion model are step frequency (SF) and step length (SL). SL is determined by a predictive model derived by the KBS during the system's calibration/training period. SL is correlated with several sensory and environmental data types, such as acceleration, acceleration variation, SF, terrain slope, operator's height, etc. that constitute the input parameters to the KBS system. The KBS-predicted SL, together with the heading information provided by the magnetometer and/or gyroscope, supports the DR navigation. The current target accuracy of the system is 3-5 m CEP (circular error probable, 50%).A summary of the performance analysis in the mixed indoor-outdoor environments, with the special emphasis on the DR performance is provided.

1. INTRODUCTION AND BACKGROUND INFORMATION

The ability to determine one's position in absolute or map-referenced terms, relative to objects in the environment, and to move to a desired destination point is an everyday necessity. Recent years brought up an explosion in the development of portable devices that support this functionality. A Personal Navigation Assistant (PNA) also known as Personal Navigation Device (PND) is a portable electronic tool, which combines the positioning and navigation capabilities, usually provided by the Global Positioning System (GPS), and possibly by other navigation sensors. The most commonly used PNAs are the hand-held GPS units, which are capable of displaying the user's location on an electronic map backdrop. This generation of PNAs (often referred to as first generation PNAs) are primarily used in leisure, marine and hiking applications. PNDs first entered the market in the early 1980's, but they were big and rather clunky systems that only contained maps of a small area. The newest generation of PNDs offers many more features, such as real-time traffic information, location of points of interest, and utilizes maps of entire continents. They offer sophisticated navigation functions and feature a variety of user interfaces including maps, turn-by-turn guidance and voice instructions that have been developed primarily for car navigation. Dead reckoning navigation using data collected by sensors attached to the drive train, such as gyroscopes and accelerometers, can be used for greater reliability, as GPS signal loss and/or multipath can occur due to urban canyons, foliage or tunnels. Currently, numerous cellular phone and PDA (Personal Digital Assistant) models have GPS-based navigation capabilities, aside from their original design as personal organizers.

It should be pointed out here that although the same navigation component is used in car and pedestrian navigation, PNDs differ from guidance systems for car navigation in many ways following from the condition that pedestrians are not tied to a road network. Thus, pedestrians are free to use either network-like systems (walkways or streets) or region-based systems with no obvious network structure (parks, train stations, stadiums, etc.). Consequently, PNDs providing route commands must go beyond network-based navigation and adapt to the variability of the surrounding environments. Hence, the underlying framework for the generation of route instructions for pedestrian navigation systems is fundamentally different than that of a car navigator. An example approach that describes the relation between the navigator and path in terms of "topological stages of closeness (SOCs), which enable a finer granularity of route instructions, and hence, the generation of more accurate route instructions" is described in (http://www.i-spatialtech.com/white_papers/region-based_pedestrian_navigation.htm). In general, this task is more complicated than its counterpart for the network-dependent navigators. However, regardless of network-dependency or independency, to guide mobile users along a route, all navigators must be able to determine their location in relation to the route. Consequently, GPS or any other navigation technology must provide a position fix and guiding algorithms, needed to determine the current location within the background map along the route taken. Any, even the most sophisticated and reliable algorithm that matches the position fix with a map will not work if there is no position fix.

1.1 Technologies, Systems and Trends

In 1999, the Federal Communication Commission (FCC) mandated that wireless carriers needed to support delivery of location information to 911 operators in the US and that service providers were permitted to use the location capabilities in the handset and the network for commercial purposes. This directly initiated the development of the wireless location-based services (LBS) market. The key players that emerged in the wireless device manufacturing industry are SnapTrack (acquired by Qualcomm in 2000; http://www.qualcomm.com/about/qct_redirect.html) and SiRF (http://www.sirf.com/). The important development for the new markets for LBS solutions was the emergence of GPS-based PND business by companies such as Garmin, Navman, Trimble, Magellan, and TomTom. The current trend is that increasingly more devices, such as, for example, the Blackberries, become connected wirelessly and provide some navigation information. Also, the iPhone launched by Apple supports Google maps on the device, and it is expected that the next generation iPhone will offer a significant improvement in geographic navigation (GPS) and management tools (http://lbs.gpsworld.com/gpslbs/article/articleDetail.jsp?id=466339&sk=&date=&pageID=2). It is also important to mention here that high quality and up-to-date digital maps are crucial to reliable personal navigation. This part of the consumer market is well covered by Navteq (http://www.navteq.com/) and Tele Atlas (http://www.teleatlas.com/index.htm) who deliver digital maps and dynamic content that power the world's demand for navigation and location-based applications.

The improvements in GPS receiver size, performance, and cost over the past few years have stimulated an upsurge of consumer GPS products, which followed an increased public awareness of the potential utility of GPS. The GPS-based consumer products, such as car navigation systems, GPS-enabled PDAs and locatable mobile phones, have flooded the marketplace. Yet, general misunderstanding of the GPS limitations often leads to consumer dissatisfaction due to the low position accuracy their devices may furnish, or a lack of any positioning information under some circumstances. Consumers expect a navigation product simply to work, regardless of the conditions and the surrounding environment.

Although high-sensitivity receivers, or assisted-GPS (A-GPS), enable operation with much weaker signals (even indoors), there are still situations where even A-GPS does not provide sufficiently accurate position fix within an acceptable time interval. Consequently, users in high multipath or extremely weak signal environments may experience low positioning accuracy and/or long delays in achieving a position fix. Even if some contingency[§] strategies, taking effect when A-GPS fails, are implemented to provide the user with a gracefully degrading position fix service, the position fix will eventually become unavailable. As much as the consumer market would like to avoid such situations, they are inevitable, unless some augmentation is used with GPS or even A-GPS. This increasingly leads to multisensor solutions that are not yet very common within the consumer market, but substantial research and conceptual work has been conducted in recent years to develop reliable and ubiquitous personal navigation device for pedestrians (e.g., Retscher 2004a and b; Retscher and Thienelt, 2004; Kourogi *et al.*, 2006; Lachapelle *et al.*, 2006) as well as military and emergency personnel (Grejner-Brzezinska *et al.*, 2006a and b, and 2007a and b; Moafipoor *et al.*, 2007), who operate in environments where GPS may not be always available, while their navigation fix is crucial for the combat or emergency mission.

Pedestrian and personal navigation[**] systems require continuous positioning and tracking of a mobile user with a certain positioning accuracy and reliability. However, navigating in urban and other GPS-impeded environments, such as mixed indoor and outdoor areas, is a very challenging task. These systems require multiple navigation technologies to be integrated together to form a multisensor system, as mentioned above, in order to serve as many different environments as possible for seamless and reliable navigation. Example technologies suitable for multisensor solutions supporting personal navigation include GNSS (Global Navigation Satellite System), ground-based RF systems, such as pseudolites (e.g., Barnes *et al.*, 2003a and b) suitable for confined and indoor environs, as well as cellular phone positioning for absolute position determination, dead reckoning sensors (e.g., magnetic compass, gyroscopes, accelerometers and barometers) to determine orientation, distance traveled and height. For location determination of a pedestrian in multi-storey buildings the Wireless Local Area Networks (WLAN) (e.g., Wang *et al.*, 2003; Li *et al.*, 2006), or transponders or beacons installed in the buildings (e.g., Pahlavan *et al.*, 2002) are increasingly used. Other indoor positioning systems include so-called Active Badge Systems (e.g., Hightower and Boriello, 2001). These methods can provide few-meter accuracy for indoor tracking and positioning. Robustness of the ultra wideband (UWB) signal to multipath fading and its high penetration capability makes it another technique suitable for indoor positioning. The indoor UWB-based navigation systems (fundamentally designed for wireless communication, navigation being usually a tag-along application), which work in the bandwidths in excess of 1 GHz, measure accurate time of arrival (ToA), the difference of ToA of the received signals for the estimation of distance to mobile user (e.g., Pahlavan *et al.*, 2002; Win and Scholtz, 2002; Ni *et al.*, 2007). The UWB ranging and communication scheme may employ one or more of the following techniques: time division multiple access (TDMA), frequency division multiple access (FDMA) or code division multiple access (CDMA). A direct sequence (DS)-CDMA scheme is a preferred UWB scheme for providing ranging resolution and identification of base stations (see, e.g., http://www.wipo.int/pctdb/en/wo.jsp?IA=US2005004936&DISPLAY=DESC for more details). Another method considered in indoor navigation is based on optical tracking systems also referred to as image-based systems. This method has been researched by, for example, Veth and Raquet (2006a and b) in connection with inertial technology. In general, the image-based tracking systems could provide high positioning accuracy and resolution, but these are a function of the type of sensors used (primarily its angular resolution), distance between the target and the sensor, specific application and the environment (outdoor vs. indoor).

[§]According to http://lbs.gpsworld.com/gpslbs/content/printContentPopup.jsp?id=262078 "The simplest fall-back method is Cell ID, by which a user's position is assumed to coincide with the location of the cell tower handling the user's call, or the centroid of the coverage area of that particular cell. In either case, the assumed user's position could be wildly inaccurate, depending on the network's tower spacing. Researchers in the United Kingdom have invented a fall-back technique that uses network signal timings to provide a user's phone (terminal) with a synthetic clock, synchronized to GPS Time. With such an accurate clock, the terminal can be positioned using a similar technique to that used by GPS but by using the network signals themselves."

[**] Personal navigation is understood here as navigation of military and emergency personnel, while pedestrian navigation refers to all other uses for location/navigation of a mobile user.

According to Li *et al.* (2006) WLAN based positioning is easily implemented in indoor environments, as its associated consumer hardware is the most readily available of all signal strength-based methods. It is also the most accurate method, as the signal strength (SS) displays high spatial variance, and WLAN chipsets are relatively easily programmed for this purpose. WLAN operates in the 2.4 GHz band, which is the only accepted ISM (Industrial, Scientific and Medical) band available worldwide license free. There are essentially two approaches to using WLAN for positioning: one uses a signal propagation model and information about the geometry of the building to convert SS to a distance measurement from the access point, followed by trilateration from multiple access points to provide the final position fixes. The second method of WLAN positioning is known as location fingerprinting. The key idea behind this approach is mapping of the location-dependent parameters of measured radio signals within the area of interest that is the received signal strength indicator (RSSI) at the access points. According to *ibid*. location fingerprinting consists of two phases, (1) training and (2) positioning. The objective of the training phase is to build a fingerprint database. The generation of the database starts with a selection of reference points (RPs) followed by measuring SS at these locations, and recording it in the database. With a sufficient number of reference points stored together with their SS characteristics, a mobile user can position himself/herself by comparing the measured SS with the reference data in the database using some search/matching algorithm. Naturally, the accuracy of the fingerprinting method increases with the increasing number of RPs.

Technique/sensor	**Navigation information**	**Typical accuracy**	**Selected characteristics**
GPS/GNSS • Position coordinates • Velocity	X,Y,Z V_x, V_y V_z	~10 m (1-3 m DGPS) ~0.05 m/s ~0.2 m/s	• Line-of-sight system • Results in a global reference system
Pseudolites	X,Y,Z V_x, V_y, V_z	Comparable to GPS	• Line-of-sight system • Operate at GPS and non-GPS frequencies
WLAN • Signal strength-based method • Fingerprinting method	X,Y,Z X,Y,Z	2-6 m 1-3 m	• Indoor positioning in a local system • Signal attenuation due to distance, penetration through walls and floors, and multipath • Interference from other users of 2.4GHz frequency band
UWB	X,Y,Z	dm-level accuracy theoretically achievable at 10-20 m range[††]	• Resistant to multipath fading • Strong signal penetration • Possible interference with GPS • Positioning approach similar to WLAN
Mobile phone positioning	X, Y	50-300 m	• Cell-ID positioning approach (lower accuracy range) • Time of arrival or difference in time of arrival used to derive range or range difference
Dead reckoning system	X, Y Z Heading φ	20-50 m/1 km 3 m 1°	• Relative positioning • Sensors require calibration
Direction of motion • Digital compass/magnetometer	Heading φ	0.5° - 3°	• Long term accuracy stability • Subject to magnetic disturbances • Sensitive to tilt
• Gyroscope			• Short term accuracy stability • Not subject to external disturbances • Subject to drifts • Should be calibrated when GPS is available
Accelerometer	a_{tan}, a_{rad}, a_z	<0.03 m/s^2	• Subject to drifts • Should be calibrated when GPS is available
Digital barometer	Z	1-3 m	• Requires calibration by a given initial height to provide heights with respect to, for example, WGS84 ellipsoid
Optical systems • Image based • Optical sensor network • Laser	X, Y, Z X, Y (Z optional) X,Y, Z	few meters few meters cm to dm	• Line-of-sight system • Network approach is geometry-depended • Image overlap required for 3D • Local or global reference system

Table 1. Typical sensors used in personal navigation: observables and their characteristics (Retscher and Thienelt, 2004; modified and extended); where X,Y,Z are the 3D coordinates, v_x, v_y, v_z are the 3D velocities, φ is the direction of motion (heading) in the horizontal plane XY, a_{tan} is the tangential acceleration and a_{rad} is the radial acceleration in the horizontal plane XY, a_z is the vertical acceleration.

[††] See, Ni *et al.* (2007)

Other optical tracking systems that can be potentially used for personal tracking make use of light to measure angles (ray direction) that are used to find the position location (however, to the best of the authors' understanding, no system has been reported so far to use this techniques for personal navigation). The essential parts of an optical system are the target (mobile user) and the detector (sensor). These systems rely on a clear line-of-sight (LOS) between the detector and the target. Detectors can be in the form of Charged Coupled Device (CCD)-based cameras, video cameras, infrared cameras, etc. Targets can be active, such as light-emitting diode or infrared-emitting diode, or passive, such as mirrors or other reflective materials, or simply natural objects (Allen ***et al.***, 2001). Detectors are used to observe targets and to derive position and orientation of a target from multiple angular observations (multiple detectors). It is necessary to mention here another type of optical tracking systems, based on laser ranging, which provides range measurements to active or passive targets. This method is well suited for measuring distances from several meters to a few hundreds of meters, and even considerably longer distances, and thus, it is suitable for both outdoor and indoor applications. The accuracy of the distance measured ranges from micrometers for short-range devices, to a decimeter-level for very long-range systems (see, e.g., Soloviev ***et al.***, 2007, for urban navigation application of this technique).

1.2 Navigation of Pedestrians vs. Military and Emergency Personnel Navigation

Over the past decade, due to the widespread use of GPS, the US military has become increasingly dependent on precision navigation and timing (PNT). Military strategy and tactics have evolved to assume the availability and integrity of accurate position, navigation and timing information based on GPS. In fact, one of the key enablers of precision and net-centric warfare is high-accuracy PNT, currently predominantly provided by GPS. One of the crucial applications of PNT is accurate and reliable navigation and tracking of ground personnel in combat and emergency situations. Protecting ground troops or emergency/disaster management crews, while maintaining the effectiveness of the combat or rescue operation, requires precise individual geolocation of all military and emergency personnel in real-time.

However, GPS is not effective in electromagnetically and physically impeded environments. There are also environments where GPS is significantly degraded or not available. Unfortunately, with the global war on terror, the military operations have become more focused on these types of environments. Thus, there is an urgent need to develop autonomous robust navigation theories and algorithms that provide assured GPS-level performance in all environments, thereby extending the reach of precision combat into these hard-to-navigate, high-importance areas. While the integration of Inertial Navigation System (INS) data with GPS data is a common navigation solution in use today, the PNT performance of GPS/INS systems can degrade rapidly when GPS is not available. The development of lower-cost, high-accuracy imaging and ranging devices, e.g., digital cameras, scanning Light Detection And Ranging (LiDAR), flash-LADAR (LAser Detection And Ranging), mm-wave RADAR, and more, have shown promise in providing information which can be used to aid a GPS/INS system in urban environments where GPS signals may be blocked by topography or denied by interference. Currently, a significant body of research is underway to address the problem of assured navigation in all environments. However, it is a difficult and complex problem, which requires a multidisciplinary approach to address the fundamental challenges that must be overcome to realize a truly autonomous assured navigation and timing capability. This paper only touches one aspect of this complex problem – personal multisensor navigation, where in addition to a number sensors listed in Table 1, human body is also considered as a sensor, and its dynamic modeling is used to support dead reckoning navigation mode in situations where all other sensors may fail.

2. PERSONAL NAVIGATOR BASED ON HUMAN LOCOMOTION MODEL

2.1 Human Body as Navigation Sensor

Recent years brought many new developments in computational intelligence (CI) techniques leading to an exponential increase in the number of applications in numerous areas, such as engineering, social and biomedical. In particular, CI techniques are very suitable in applications related to human motion modeling, and are being increasingly used for this purpose, due mainly to the complexity of the biological systems as well as the limitations of the existing quantitative techniques in modeling. Examples of algorithms and methods used in CI are Artificial Neural Networks (ANNs) and Fuzzy Logic (FL). Using CI methods allows for better process control and more reliable prediction/modeling of the processes under consideration. In our case, the ANN (e.g., Kaygisiz *et al*., 2003; Chiang *et al*., 2003; Wang *et al*., 2006; Grejner-Brzezinska *et al*., 2006c and 2007a and b; Moafipor ***et al.,*** 2007) and FL (e.g., Sasiadek and Khe, 2001; Kosko, 1991) are used to model a simplified human dynamics model that consists of step length (SL) and step frequency (SF), which together with the direction of motion (step direction, SD) are used to navigate the mobile operator in the dead reckoning mode. The human dynamics model is calibrated while other sensors, primarily GPS, provide continuous navigation solution, and the human-based sensors are used in situation where other sensors cease to operate (Grejner-Brzezinska ***et al.***, 2006a-c; 2007a and b; Moafipoor 2007a and b; Toth ***et al.,*** 2007).

In the current concept design, the prototype of a personal navigator is based on multi-sensor integration in a backpack configuration, augmented by the human locomotion model that supports navigation during GPS gaps. The navigation accuracy requirement is at 3-5 m CEP (circular error probable) 50% level. At the current stage of the research, the algorithmic concept of the GPS-based, IMU-augmented personal navigator system with an open-ended architecture has been implemented (see Figure 1).

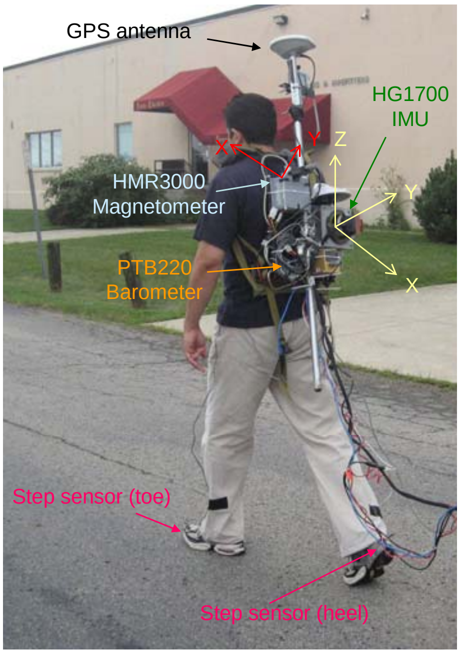

Figure 1. Personal navigator: sensor configuration.

At present, the following sensors are used: dual frequency Novatel OEM4 GPS receiver with, Honeywell tactical grade HG1700 IMU (gyro rate bias ~3-5 °/hr, and accelerometer bias of 2.0 mg) impact foot switches used for timing the user's step events, PTB220A barometer (500–1100hPa pressure range, -40–140F temperature range, 0.5–10Hz update rate, 0.1–3s output averaging time, and 1.5 m height accuracy (1 sigma)) and a three-axis Honeywell HMR3000 magnetometer with an integrated pitch-roll sensor; up to 20 Hz read-out rate, 1º (level), and 2º (tilt) heading accuracy (1 sigma). The GPS carrier phase and/or pseudorange measurements in the double difference (DD) mode[‡‡], undifferenced pseudorange or ionosphere-free linear combination of P1P2 pseudoranges, barometric height, compass (magnetometer) heading, inclinometer (magnetometer) pitch/roll, and the INS-derived position and attitude information are integrated together in the tightly coupled Extended Kalman Filter with 29 states listed in Tables 2-3.

Sensor	Error Sources	Stochastic Error Model
Accelerometer	Bias	Random walk
	Scale factor	Random constant
Gyroscope	Bias	Random walk
	Scale factor	Random constant
Barometer	Bias	Random walk
	Scale factor	Random constant
Magnetometer (compass)	Bias	Random walk
	Scale factor	Random constant

Table 2. Stochastic error models for multi-sensor error sources (Grejner-Brzezinska *et al.*, 2007b).

[‡‡] This measurement type is of the highest accuracy and provides the best calibration results, but requires data transfer from a reference base in real time. Pseudorange-based stand alone solution is the simplest, but the least accurate approach.

The barometer and compass are introduced to aid height and heading estimation, respectively, when GPS signals are blocked. These sensors (as well as the IMU and human dynamics model) are continuously calibrated when GPS signals are available. While forming the theoretical foundations of this multi-sensor system and developing the algorithmic concept, an open-ended design architecture was considered, which should allow the next level of implementation, such as the inclusion of miniaturized imaging sensors, e. g., digital and infrared cameras or laser range finders. It should also be mentioned that precise timing of all sensory data to GPS time is crucial to sensor/data integration. Essentially, the GPS time must be externally recovered from 1PPS (pulse per second) signal, available through a standard interface from a GPS receiver.

2.2 System Design Architecture

The system's design architecture is shown in Figure 2, where the three primary modes of operation are indicated (1) calibration mode, available during the GPS signal reception; it represents the initial sensor calibration and KBS calibration/training; (2) hybrid navigation mode, when multi-sensor assembly is used to navigate; since GPS is available, continuous sensor and KBS calibration is also performed; and (3) DR navigation mode, which kicks in when GPS is blocked. A ZUPT static calibration mode is also included that may be applied for partial calibration of the IMU sensors if the operator may remain stationary for some time period (several seconds to a few tens of seconds usually suffice).

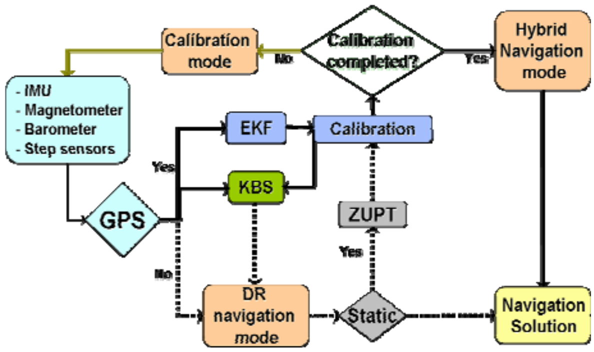

Figure 2. Personal navigator: modes of operation.

State vector components (number of states)		Initial Covariance Matrix Components	Stochastic Model, White Noise
Position (3)		100 m	RC, 0
Velocity (3)		1 m/s	RW, 5 μg
Attitude (3)	Pitch, Roll	1°	RW, 0.001 °/√hr
	Heading	2°	
Accelerometer Bias (3)		1 mg	RW, 20 μg/ √hr
Accelerometer Scale Factor (3)		120 ppm	RC, 0
Gyro Bias (3)		1°/hr	RW, 0.125 °/√hr
Gyro Scale Factor (3)		10 ppm	RC, 0
Barometer Bias (1)		1 m	RW, 0.1 m
Barometer Scale Factor (1)		1	RC, 0
Magnetometer Compass Bias (3)		1°	RW, 1°
Magnetometer Compass Scale Factor (3)		1	RC, 0

Table 3. State vector components and their stochastic characteristics; (RC): Random constant, (RW): Random walk, (mg) stands for $10^{-3} \cdot g$, (μg) stands for $10^{-6} \cdot g$, and g is the gravity constant (Grejner-Brzezinska et al., 2007b).

ANN input parameters	Without PCA		With PCA	
	Training Mean ± Std [cm]	Testing Mean ± Std [cm]	Training Mean ± Std [cm]	Testing Mean ± Std [cm]
SF, |a|, Var(|a|), Slope	2.3 ± 4.9	7.1 ± 5.0	0 ± 0.3	1.5 ± 1.7

Table 4. The effect of PCA transformation on SL determination using ANN in training and testing modes; mean and std of the differences between the reference (known) SL and ANN-predicted SL; no reduction of the parameter space applied.

Solution type	Mean [m]	Std [m]	Max Difference [m]	End Misclosure [m]	CEP 50% [m]	CEP 95% [m]
DR without PCA	1.7	1.4	4.7	2.3	1.3	4.4
DR with PCA	0.33	0.32	1.07	1.16	0.3	1.0

Table 5. Statistical fit to reference trajectory of DR trajectory generated with SL predicted by ANN with and without PCA transformation (no parameter space reduction); circular trajectory of ~45 m.

The ANN and FL modules designed for handling the human locomotion model, form a Knowledge-Based System (KBS). The ANN component consists of a single-layer network with Radial Basis Function (RBF) and up to six input parameters that contain the information about the step length (SL), such as step frequency (SF), peak-to-peak mean acceleration (|a|), peak-to-peak variation in acceleration (Var|a|), terrain slope, change in barometric height during a single gait cycle (Δh_{Baro}), and operator's height; currently, a Gaussian function (G) is used as RBF. Since the input parameters are correlated, Principal Component Analysis (PCA) is applied to decorrelate the input parameters and to determine the minimum sufficient set of parameters that should be used as input to the ANN. The accuracy of SL prediction based on this module is at the cm-level (refer to Tables 4 and 5 for examples of the PCA-transformation impact on LS modeling results; for more details, see, Grejner-Brzezinska *et al.,* 2006b, c, and 2007b). This accuracy of SL prediction allows trajectory recovery well within the 3-5 m CEP if accurate heading is provided (HG1700 heading is sufficient within a few minute GPS gap). The trajectory can be recovered in 2D, based on the SL only ($\Delta x = \sum_{k=1}^{n} SL_k \sin Az_k$ and $\Delta y = \sum_{k=1}^{n} SL_k \cos Az_k$, where Az is the heading provided by either gyro or magnetometer or both and n is the number of steps along the trajectory); if calibrated barometer measurements are used, the solution is provided in 3D.

Table 6 lists all of the measurements delivered by the sensors used in the current prototype, which can constitute input parameters to the KBS to parameterize the body locomotion and SL approximation functions.

Sensor	Sensor Measurements
Accelerometer	- Step events - $\|a\|_{xyz}$, $\|a\|_{xy}$, $\|a\|_z$ -Var($\|a\|_{xyz}$), Var($\|a\|_{xy}$), Var($\|a\|_z$) - Max(|a|) , Min(|a|) - Tilt (roll and pitch angles at rest)
Gyroscope	- Angular rate - Roll, pitch, heading
Compass	- Angular rate - Heading
Barometer	- Var(Δh) - ∑(|Δh|) - Altitude
Step sensors	- Step events
External data	- Person's height, age, weight

Table 6. Sensors and body locomotion parameterization (Moafipoor *et al.,* 2007a).

In Table 6, $|a|_{xyz}$, $|a|_{xy}$, and $|a|_z$ are magnitudes of the acceleration vector during a single step in 3D, horizontal, and down directions, respectively; Var($|a|_{xyz}$), Var($|a|_{xy}$), and Var($|a|_z$) are the corresponding variance of the acceleration vector; Max(|a|) and Min(|a|) are the maximum and minimum values of the acceleration for each pace.

An alternative implementation of the SL/SD calibration/prediction module is based on FL (see, Moafipoor *et al.*, 2007a for details of this algorithm). By incorporating Fuzzy Logic to our KBS, better process control is facilitated, as this approach allows an easy addition of constraints, such as, for example hallway layout for indoor navigation, or digital map information, which are difficult to handle in "regular" EKF environment. Fuzzy Logic can be described simply as "computing with words rather than numbers," and Fuzzy Logic control can be described as "control with sentences rather than equations" (Sasiadek and Khe, 2001). Rule-based Fuzzy Logic provides a formal methodology for linguistic rules resulting from reasoning and decision making with uncertain and imprecise information. In fuzzy behavior-based navigation the problem is decomposed into simpler tasks (independent behaviors), and each behavior is composed of a set of Fuzzy Logic rule statements aimed at achieving a well defined set of objectives; example rules are:

$$\text{Rule } (i)\text{: } \textit{If } x_{i1} \textit{ is } A_{i1} \textit{ AND } x_{i2} \textit{ is } A_{i2}, \ldots, \textit{AND } x_{im} \textit{ is } A_{im} \textit{ THEN } y \textit{ is } B_i \quad (1)$$

where $i=1,\ldots,n$, and n is the number of rules in a given fuzzy rule base; $j=1,..,m$, and m is the number of antecedents; x_{ij} are the input variables, premise variables, which are the sensor data of the mobile user; A_{ij} are the input fuzzy sets; and B_i is the output fuzzy set, and y is the output variable. Having multiple behaviors, which are all running concurrently, leads to situations where several command outputs may be produced simultaneously. Therefore, the main advantage of using Fuzzy Logic for navigation is that it allows for the easy combination of various behaviors through a command fusion process instead of using fixed parameters in the entire process.

The design of a Fuzzy Logic controller starts with the definition of the membership functions for the output variable, here, SL. Currently, seven empirically determined membership functions are used for SL in our prototype, as shown in Figure 3. The fuzzy language for this fuzzy set is divided into a range of quantities such as: Zero, Very Short, Short, Normal, Semi-Long, Long, and Very Long; vertical axis in Figure 3 indicates the degree of membership of SL in the corresponding fuzzy set (η_{SL}).

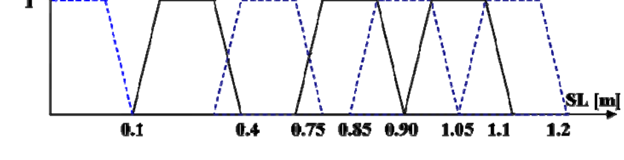

Figure 3. SL membership function.

Defining the shape, the membership functions, and the bounds of these quantities is a design problem, but the attributes of the system will not be changed significantly if the membership functions are modified slightly. The value of the membership function indicates the degree of membership of SL to the fuzzy set. If the membership value is 1 for one of the fuzzy sets, the SL is perfectly representative of the set, and if it is 0, the quantity is not at all a member of the set. Any value between 1 and 0 indicates a partial membership. A better way to make SL a fuzzy set is to allow the membership functions to change gradually from one quantity to the next one. Then, the real power of the Fuzzy logic comes from the ability to integrate these partial membership values in a way that permits a good balance between membership functions.

For reliable SL/SD results, the KBS system must be sufficiently trained, meaning that sufficient amount of calibration data must be either stored in the memory or provided during the actual navigation task, before the GPS signals are blocked. For the ANN module training, different terrains slopes/configuration and types of surfaces must be included, for a representative number of operators, to derive a reliable predictive model; obviously, if the system is calibrated under circumstance totally different from the actual navigation task, the results will be much worse than the examples provided here. Similarly, the FL modules requires a large sample of representative data where various human dynamics types are included in various environmental conditions and terrain configurations, to derive the appropriate fuzzy rules for the membership functions that will be used to predict the model parameters once GPS signals are blocked. The additional benefit of FL is that the actual behavior of the mobile operator can be predicted, that is, if the person is running, walking, stumbling, climbing, etc., and that might be useful information in particular in combat or emergency situation, and can be wirelessly transmitted to an operational center (not implemented in our prototype).

An additional use of FL in our implementation is the adaptive Extended Kalman Filter where the adaptivity scheme is based on Fuzzy Logic rules (see, e.g., Sasiadek *et al.,* 2000; Moafipoor, 2008). In this approach, the pseudorange practical covariance, $C_k = \frac{1}{m}\sum_{i=1}^{m} e_k e_k^T$, and the actual covariance (covariance of innovation) from the EKF, $S_k = H_k P_k^- H_k^T + R_k$, are compared, and the level of the difference between them is tested using fuzzy rules to decide if the measurement covariance matrix R_k should be modified (adapted to the current state of system sensors). H_k is the observation design matrix, P_k^- is the predicted covariance, and e_k is the innovation vector. The system calibration mode with the KBS module is illustrated in Figure 4.

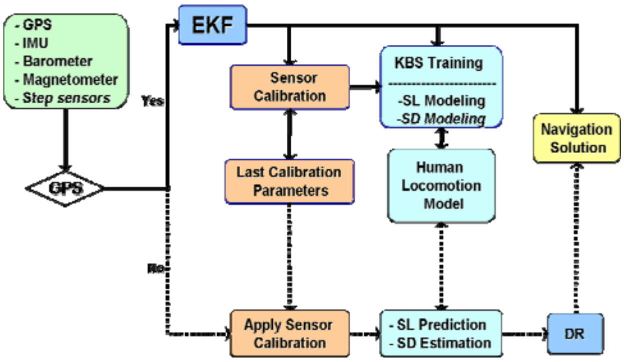

Figure 4. Personal navigator: 1) calibration mode data flow is shown in solid lines; and 2) when GPS signals are not available, the dotted lines become solid indicating that now the navigation solution is formed based on calibrated data of dead reckoning sensors, including the human locomotion model parameter, step length (SL) and step direction (SD).

3. PERFORMANCE ASSESSMENT

The personal navigator in the hybrid and DR modes has been extensively tested using various operators, different terrain configuration and mixed outdoor-indoor environments. The details of the performance test to date were provided in (Grejner-Brzezinska *et al.,* 2006a-c; 2007a and b; Moafipoor 2007a and b; Toth *et al.,* 2007), and only summary statistics are presented here, with the emphasis on the newest results of the mixed indoor-outdoor setting.

In this experiment, data were collected in the parking lot and inside the Center for Mapping building on August 21 and 26, 2007. The operators, S and E, walked the parking lot and hallways of the Center for Mapping, and made several loops following the marked control points in the hallways of this single-storey building. A floor plan of the building was previously acquired by classical surveying methods, and control points were established in the hallways with the accuracy better than 1-2 cm in E and N, and 5 mm in height. The main objective of the control points was to facilitate the prediction of the user's position and provide control for the reference trajectory inside the building where no GPS was available. By the time the operators started walking inside the building, they had completed outside calibration procedures during normal GPS signal availability (using DD carrier phase and pseudorange measurements), which was required for a better performance of the other sensors (see Figure 5).

Inside the building, the heading was estimated from the HMR3000 magnetometer compass and HG1700 gyro. The altitude was measured by the PTB220 barometer, which was calibrated against the known pressure standards (pressure, temperature, etc.) for the general area of activity. It was observed that after completing the initial calibration, these sensors showed performance that ensured redundant and complementary measurement inputs, as well as sufficient stability along the trajectories studied here.

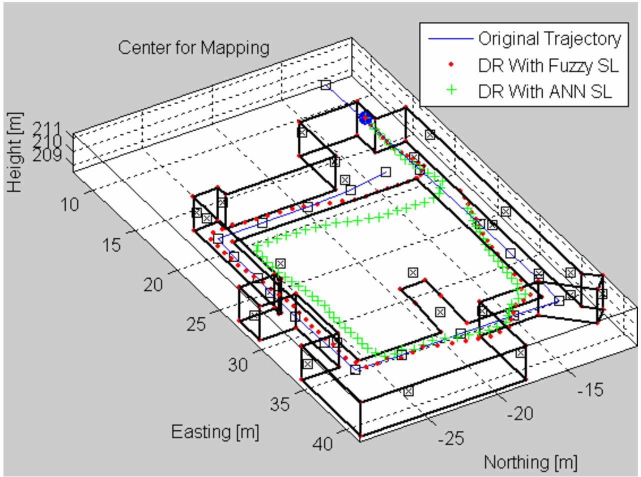

Figure 5a. Center for Mapping floor plan and DR trajectory reconstruction for operator S using compass heading.

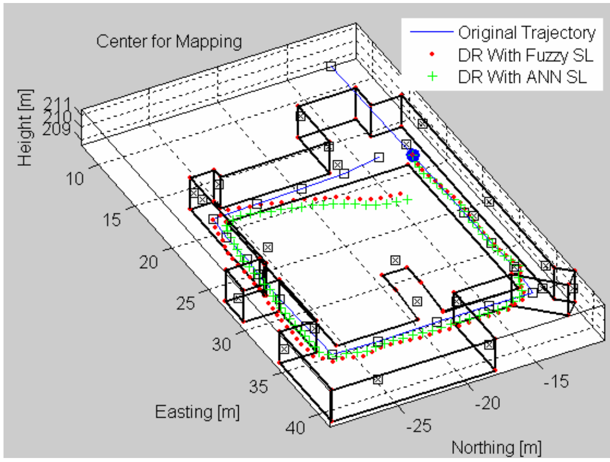

Figure 5b. Center for Mapping floor plan and DR trajectory reconstruction for operator E using compass heading.

Tables 7 and 8 show the accuracy assessment of the indoor DR trajectory for one full loop along the Center for Mapping hallways, and Table 9 provides the statistics of the three complete indoor loops. This test represents the combination of outdoor and indoor environments; 350 s of outdoor sensor calibration was followed by three complete indoor loops in three minutes (Aug. 26 dataset), using gyro/compass heading. As can be seen in Table 9, three indoor loops are still viable within the 3-5 m CEP50 constraint.

Test data set	SL model	Mean [m]	Std [m]	Max [m]	End Misclosure [m]	CEP (50%) [m]
Operator S	Fuzzy	0.78	0.87	1.61	2.18	0.49
	ANN	1.24	0.75	1.88	2.14	1.17
Operator E	Fuzzy	0.84	0.81	1.95	2.75	0.73
	ANN	0.80	0.56	1.45	1.94	0.77

Table 7. Statistical fit to reference trajectory of the indoor DR trajectories generated using SL predicted with fuzzy logic and ANN, and compass heading; one indoor loop.

Test data set	SL model	Mean [m]	Std [m]	Max [m]	End Misclosure [m]	CEP (50%) [m]
Operator S	Fuzzy	0.43	0.92	1.17	1.42	0.45
	ANN	0.41	0.54	1.07	1.10	0.43
Operator E	Fuzzy	0.59	0.43	1.25	1.14	0.59
	ANN	0.62	0.47	1.11	1.26	0.65

Table 8. Statistical fit to reference trajectory of the indoor DR trajectories generated using SL predicted with fuzzy logic and ANN, and gyro heading; one indoor loop.

Test data set	SL model	Mean [m]	Std [m]	Max [m]	End Misclosure [m]	CEP (50%) [m]
327 m	Fuzzy	1.57	1.78	4.66	3.32	2.94
	ANN	1.15	1.57	4.52	2.6	2.53

Table 9. Statistical fit to reference trajectory of the indoor DR trajectories generated using SL predicted with fuzzy logic and ANN, and gyro/compass heading; three full indoor loops.

An example outdoor trajectory, where DR solution was also tested after a deliberate removal of the GPS signals, is illustrated in Figure 6, and Table 10 presents the resulting accuracy statistics.

Test data set	SL model	Mean [m]	Std [m]	Max [m]	End Misclosure [m]	CEP (50%) [m]
187 m	Fuzzy	1.74	0.93	4.14	2.19	1.46
	ANN	2.05	1.06	4.53	3.01	1.97

Table 10. Statistical fit to reference trajectory of the outdoor DR trajectories generated using SL predicted with fuzzy logic and ANN, and gyro/compass heading.

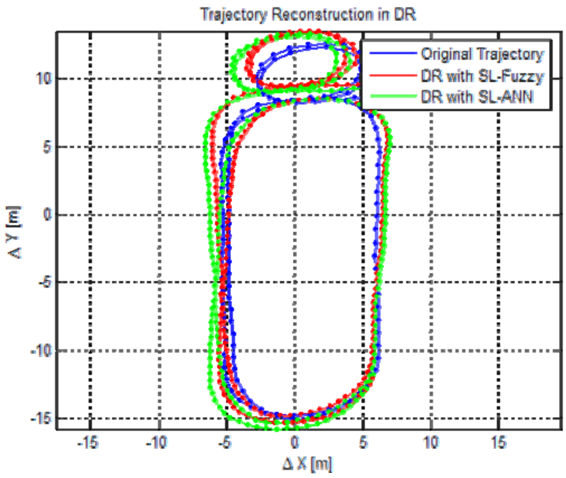

Figure 6. Reference using GPS/IMU carrier phase solution and DR trajectory reconstructed using SL determined by FL and ANN modules with gyro/compass heading.

4. SUMMARY AND CONCLUSIONS

An overview of the navigation techniques suitable for personal navigation was presented, followed by a description of an example implementation based on the multisensor integration approach, using GPS, INS, magnetometer, barometer and human dynamics model. All tests to date (outdoor and indoor environments) provided performance within the required specifications that is below 5 m CEP50; the indoor navigation, based on data collected to date, was limited to about 3 minutes. More tests are underway that consider longer and more complex indoor paths, including stairways, as this scenario has not been tested yet. The system's operational environment has been originally designed for outdoor and moderately confined environments; however, if this is to be extended to indoor environment, additional sensors might be needed, as the human dynamics alone may not facilitate reliable navigation for more extended periods of time. Since the system is designed for emergency and military crews, it cannot be expected the any wireless infrastructure will be readily available, so the sensor of choice should be based on imaging techniques that do not require any additional infrastructure.

ACKNOWLEDGEMENTS

This research is supported by a 2004 National Geospatial-Intelligence Agency NURI project.

REFERENCES

Barnes, J., Rizos, C., Wang, J., Small, D., Voigt, G., & Gambale, N., 2003a. Locata: A new positioning technology for high precision indoor and outdoor positioning. *Proceedings, ION GNSS*, September 9-12, Portland, OR, USA, CD ROM, pp. 1119-1128.

Barnes, J., Rizos, C., Wang, J., Small, D., Voigt, G., & Gambale, N., 2003b. High precision indoor and outdoor positioning using LocataNet. *Proceedings, Int. Symp. on GPS/GNSS*, 15-18 November, Tokyo, Japan, CD ROM, pp. 9-18

Chiang, K., Noureldin, A., El-Sheimy, N., 2003. Multi-sensor integration using neuron computing for land-vehicle navigation. *GPS Solutions*, 6 (4), pp. 209-218.

Grejner-Brzezinska, D.A., Toth, C.K., Moafipoor, S., Jwa, Y., 2006a. Multi-sensor personal navigator supported by human motion dynamics model. *Proceedings, 3rd IAG Symposium on Geodesy for Geotechnical and Structural Engineering/12th FIG Symposium on Deformation Measurements*, May 22-24, Baden, Austria, CD ROM.

Grejner-Brzezinska, D.A., Toth, C.K., Jwa, Y., and Moafipoor, S., 2006b. Seamless and reliable personal navigator. *Proceedings, ION Technical Meeting*, January 18-20, Monterey, CA, USA, CD ROM, pp. 597-603.

Grejner-Brzezinska, D.A., Toth, C. K., Jwa, Y., Moafipoor, S., Kwon, J., 2006c. Multi-sensor personal navigator: system design and calibration. *Proceedings, Joint Symposium of Seoul Metropolitan Fora & Second International Workshop on Ubiquitous Pervasive and Internet Mapping*, October 23-25, Seoul, Korea, CD ROM, pp. 126-137.

Grejner-Brzezinska, D.A., Toth, C.K., and Moafipoor, S., 2007a. Adaptive knowledge-based system for personal navigation in GPS-denied environments. *Proceedings, ION National Technical Meeting*, January 22-24, San Diego, CA, USA, CD ROM, pp.517-521.

Grejner-Brzezinska, D.A., Toth, C.K., Moafipoor, S., 2007b. Pedestrian tracking and navigation using adaptive knowledge system based on neural networks and fuzzy logic. *Journal of Applied Geodesy*, 1(3), pp. 111-123 (invited).

Kaygisiz, B. H., Erkmen, A. M., Erkmen, I., 2003. GPS/INS enhancement using neural networks for autonomous ground vehicle applications. *Proceeding, International Conference on Intelligent Robots and Systems*, October 27-31, Las Vegas, NE, USA, Vol. 3, pp. 3763-3768.

Kim, J.W., Jang, H. J., Hwang, D-H., Park, C., 2004. A step, stride and heading determination for the pedestrian navigation system. *Journal of Global Positioning Systems*, 3(1-2), pp. 273-279.

Kosko, B., 1991. *Neural networks and fuzzy systems*. 2nd edition, Prentice-Hall.

Kourogi, M., Sakata, N., Okuma, T., Kurata, T., 2006. Indoor/outdoor pedestrian navigation with an embedded GPS/RFID/self-contained sensor system. *Proceedings, 16th International Conference on Artificial Reality and Telexistence (ICAT2006)*, November 29-December 1, Hangzhou, China, pp. 1310-1321.

Lachapelle, G., Godha, S., Cannon, M.E., 2006. Performance of integrated HSGPS-IMU technology for pedestrian navigation under signal masking. *Proceeding, European Navigation Conference*, May 8-10, Royal Institute of Navigation, ENC-GNSS, Manchester, U.K, pp. 1-24.

Li, B., Salter, J., Dempster, A.G., Rizos, C., 2006. Indoor positioning techniques based on wireless LAN. *Proceedings, 1st IEEE International Conference on Wireless Broadband and Ultra Wideband Communications,* March 13-16, Sydney, Australia, CD ROM, paper 113.

Moafipoor, S., 2008. Adaptive Kalman filtering for personal navigation system. presented at the *2nd Annual Workshop of the Consortium of Ohio Universities on Navigation and Timekeeping (COUNT),* The Ohio State University, USA, April 7-8, 2008.

Moafipoor, S., Grejner-Brzezinska, D. A., Toth, C.K. 2007a. A fuzzy dead reckoning algorithm for a personal navigator. *Navigation* (in review, invited); also, in *Proceedings, ION GNSS 2007*, Fort Worth, TX, USA, September 25-28, CD ROM, pp.48-59.

Moafipoor, S., Grejner-Brzezinska, D.A., Toth, C.K. 2007b. Adaptive calibration of a magnetometer compass for a personal navigation system. *Proceedings, International Global Navigation Satellite Systems Society IGNSS Symposium*, December 4-6, The University of New South Wales, Sydney, Australia, CD ROM.

Ni, J. D. Arndt, Ngo, P. Phan, C., Gross, J., 2008. Ultra-wideband two-cluster tracking system design with angle of arrival algorithm. (http://ieeexplore.ieee.org/iel5/10871/34214/01631789.pdf?isnumber=34214&prod=CNF&arnumber=1631789&arSt=+6+pp.&ared=&arAuthor=Ni%2C+J.%3B+Arndt%2C+D.%3B+Ngo%2C+P.%3B+Phan%2C+C.%3B+Gross%2C+J) (accessed 15 Apr. 2008).

Pahlavan K., Li, X., Mäkelä, J.-P., 2002. Indoor geolocation science and technology, *IEEE Communications Magazine*, February, pp. 112-118.

Retscher G., 2004a. Multi-sensor systems for pedestrian navigation and guidance services. *Proceedings, 4th Symposium on Mobile Mapping Technology*, March 29-31, Kunming, China, CD ROM.

Retscher G., 2004b,. Multi-sensor systems for pedestrian navigation, *Proceedings, ION GNSS 2004*, September 21-24, Long Beach, CA, USA, CD ROM, pp. 1076-1088.

Retscher, G. and Thienelt, M., 2004. NAVIO – A navigation and guidance service for pedestrians, *Journal of Global Positioning Systems*, 3(1-2), pp. 208-217.

Sasiadek, J.Z., Khe, J., 2001. Sensor fusion based on Fuzzy Kalman filter. Proceedings, *IEEE Second International Workshop on Robot Motion and Control*, October 18-20, Bukowy Dworek, Poland, pp. 275-283.

Sasiadek, J.Z., Wang, Q., and Zeremba, M.B., 2000. Fuzzy adaptive Kalman filtering for INS/GPS data fusion. *Proceeding, 15th IEEE International Symposium on Intelligent Control* (ISIC 2000), July 17-19, Rio Patras, Greece, pp. 181-186.

Soloviev, A., Bates, D., van Graas, F., 2007. Tight coupling of laser scanner and inertial measurements for a fully autonomous relative navigation solution. *Proceedings, ION NTM*, January 22 - 24, San Diego, CA, USA, CD ROM, pp. 1089 – 1103.

Toth, C.K., Grejner-Brzezinska, D.A., Moafipoor, S., 2007. Pedestrian tracking and navigation using neural networks and fuzzy logic. Proceedings, *IEEE International Symposium on Intelligent Signal Processing*, October 3-5, Alcala De Henares, Madrid, Spain, CD ROM, pp. 657-662.

Veth, M., Raquet, J., 2006a. Two-dimensional stochastic projections for tight integration of optical and inertial sensors for navigation. *Proceeding, ION National Technical Meeting*, January 18-20, Monterey, CA, USA, CD ROM, pp. 587-596.

Veth, M., Raquet, J., 2006b. Fusion of low-cost imaging and inertial sensors for navigation. *Proceedings, ION GNSS*, September 26-29, Forth Worth, TX, USA, CD ROM, pp. 1093-1103.

Wang, Y., Jia, X., Lee, H.K., and Li, G.Y. 2003. An indoor wireless positioning system based on WLAN infrastructure. *6th Int. Symp. on Satellite Navigation Technology Including Mobile Positioning & Location Services*, July 22-25, Melbourne, Australia, CD ROM, paper 54.

Wang, J. J., Wang, J., Sinclair, D., Watts, L., 2006,. A neural network and Kalman filter hybrid approach for GPS/INS integration. *Proceedings, 12th IAIN Congress & 2006 International Symposium on GPS/GNSS*, October 18-20, Jeju Island, Korea, pp. 277-282.

Win, M.Z. and Scholtz, R. A., 2002. Characterization of ultra-wide bandwidth wireless indoor channels: a communication-theoretic view. *IEEE Journal on Selected Areas in Communications*, 20(9), December, pp. 1613-1627.