International Global Navigation Satellite Systems Society
IGNSS Symposium 2007

The University of New South Wales, Sydney, Australia
4 – 6 December, 2007

Adaptive knowledge based system based on artificial neural networks and fuzzy logic for pedestrian navigation

Dorota A. Grejner-Brzezinska
Department of Civil and Environmental Engineering and Geodetic Science
Satellite Positioning and Inertial Navigation (SPIN) Laboratory
The Ohio State University
Tel. +1-614-292-8787, Fax. +1-614-292-2957
dbrzezinska@osu.edu

Charles Toth
Center for Mapping
The Ohio State University
Tel. +1-614-292-7681, Fax. +1-614-292-8062
toth@cfm.ohio-state.edu

Shahram Moafipoor (3)
Department of Civil and Environmental Engineering and Geodetic Science
Satellite Positioning and Inertial Navigation (SPIN) Laboratory
The Ohio State University
Tel. +1-614-292-7681, Fax. +1-614-292-8062
shahram@cfm.ohio-state.edu

ABSTRACT

This paper discusses design, implementation and performance analyses of the multi-sensor personal navigator prototype, currently under development at The Ohio State University Satellite Positioning and Inertial Navigation (SPIN) Laboratory. The key component of the system architecture is a simplified dynamic model of human locomotion used for navigation in the dead reckoning (DR) mode. An adaptive Knowledge-Based System (KBS), based on Artificial Neural Networks (ANN) and Fuzzy Logic (FL), is implemented to support this functionality. The KBS is trained during the availability of GPS signals, and supports DR navigation in confined and GPS-denied environments. The primary human locomotion parameters used are step length (SL) and step frequency (SF); step frequency is extracted from GPS-timed step-sensors located in the shoe soles of the operator. SL is correlated with several data types, such as acceleration, acceleration variation, SF, terrain slope, etc., collected by the sensor assembly of the personal navigator; these parameters constitute the input to the KBS, which provides the SL estimate. The KBS-predicted SL together with heading information provided by a magnetometer and/or gyro, support the DR navigation. The target accuracy of the system is 3-5 m CEP50 (circular error probable). This paper addresses the design architecture of the integrated system and its performance analysis, with the special emphasis on DR navigation supported by the human locomotion model. In particular, the comparison of the navigation performance of two independent KBS modules based on ANN and FL is discussed.

KEYWORDS: Personal navigation, knowledge systems, neural networks, fuzzy logic

1. INTRODUCTION

Real-time positioning, navigation and tracking technology that can operate in the indoor and outdoor environments with high accuracy, and at low cost, is the ultimate goal for many ongoing research activities. In recent years, continued improvements in GPS receiver size, performance, sensitivity, and cost have stimulated an explosion of consumer GPS products, such as car navigators and pedestrian navigators. Telematics systems, locatable mobile phones, GPS-enabled PDAs, and more novel products and applications are announced almost daily. Yet many consumers are dissatisfied by the low position accuracy of their devices under some circumstances – if indeed they can obtain a position at all. In order to meet the growing demand of the military applications, as well as the consumer market requirements for accuracy, reliability and continuity, regardless of the environment, i.e., indoor or outdoor, GPS must be supported by other navigation means that can facilitate seamless navigation in confined environment. An idea of a portable device that can provide navigation and timing information regardless of location, weather and other environmental conditions is not entirely new, as personal navigators (PN) have been studied for about a decade in different fields and applications, such as visual surveillance, rescue operations, security and emergency services, police safety and military applications, and recently, the consumer market. The common goal of all these applications is to provide precise and reliable position/velocity/heading information of an individual in various environments. When line of sight to several GPS satellites is clear either GPS alone or an integrated GPS/IMU (Inertial Measurement Unit) system can provide the basic navigation functionality, with the accuracy depending on the choice of GPS and IMU sensors. In confined environments, however, the main challenge for a personal navigator is to design and implement an alternative system that will maintain the navigation performance.

In a number of civilian applications, such as pedestrian tracking or navigation, the environment can be prepared to handle losses of GPS lock by creating a smart environment using active tracking technology, such as RF signals or RFID tags, e.g., Cho *et al.*, 2003; Kourogi *et al.*, 2003. Other techniques that can be effectively used in this application are pseudolites (e.g., Kee *et al.*, 2000; Soon et al., 2003; Barnes et al., 2003), high-sensitivity GPS receivers (Lachapelle *et al.*, 2006) or assisted GPS (A-GPS). However in many applications, such as military or rescue operations, it is virtually impossible to prepare the environment in advance to fit the needs of non-GPS-based active navigation systems. Consequently, in those environments, the tracking system should rely on self-contained sensors, such as accelerometers, gyroscopes, digital barometers, electromagnetic compasses and step-sensors, possibly augmented by a human locomotion model, to deliver relevant parameters required for Dead-Reckoning (DR) navigation, such as heading, walking distance and altitude.

This paper presents the design, implementation and performance evaluation of a multi-sensor portable navigation system intended for open and confined environments, with a special emphasis on DR navigation supported by the human locomotion model. The core of the current prototype of the system is a dual frequency GPS receiver supported by recent developments in sensor technology, such as MEMS (micro-electro-mechanical) IMU, miniaturized barometer, digital compass (and magnetometer) as well as step-sensors (micro-switches) that support pedometry component of the system. The ultimate goal is to use high-sensitivity GPS receiver (e.g., SiRF technology). The navigation goal is to achieve continuous 3-5 m CEP50 (circular error probable) accuracy, with the target application in emergency and rescue operations as well as navigation and tracking of dismounted soldiers on the ground. The system is designed in an open-ended architecture to allow future extensions of miniaturized imaging sensors, such as digital and/or infrared camera and/or laser ranging device.

2. SYSTEM DESIGN AND IMPLEMENTATION

2.1 Prototype implementation

In the present system design the following sensors are integrated in the tightly coupled Extended Kalman Filter (EKF): dual frequency Novatel OEM4 GPS receiver with TRM22020.00+GP antenna, Honeywell tactical grade HG1700 IMU (note that Crossbow MEMS IMU 400CC used initially does not meet the accuracy specifications for this project, based on the initial performance tests (see, Grejner-Brzezinska et al., 2006a, b), step sensors (micro-switches) used for timing the operator'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 pseudorange measurements in the double difference (DD) mode, barometric height, magnetometer heading, and the INS-derived position and attitude information are integrated together in the tightly coupled EKF with 27 states. The DD mode is used for performance validation and sensor calibration, while a stand-alone point positioning module has also been implemented.

Figure 1 illustrates the current prototype architecture design in (a) GPS/IMU-based navigation and human locomotion model training mode, and (b) DR navigation mode; note that magnetometer and barometer are also calibrated in mode (a) and are used in mode (b) for DR navigation. Figure 1 (top) shows the multi-sensor data stream sent to the EKF, which estimates a nine-state navigation solution and all sensor errors. The navigation solution is used to train the adaptive Knowledge Based System (KBS) that (1) acquires and stores the information about the human locomotion model (SL), and subsequently (2) uses it to navigate in dead-reckoning mode during the GPS signal blockage (see, Grejner-Brzezinska, 2006a, b), where the KBS training (or expert-derived) information together with the current sensory input in the prediction mode is used to evaluate SL to support DR navigation mode. Figure 1 (bottom) indicates that no sensor calibration is performed during DR navigation. Figure 2 illustrates the DR module of the system and Figure 3 shows the current sensor assembly in the form of a backpack.

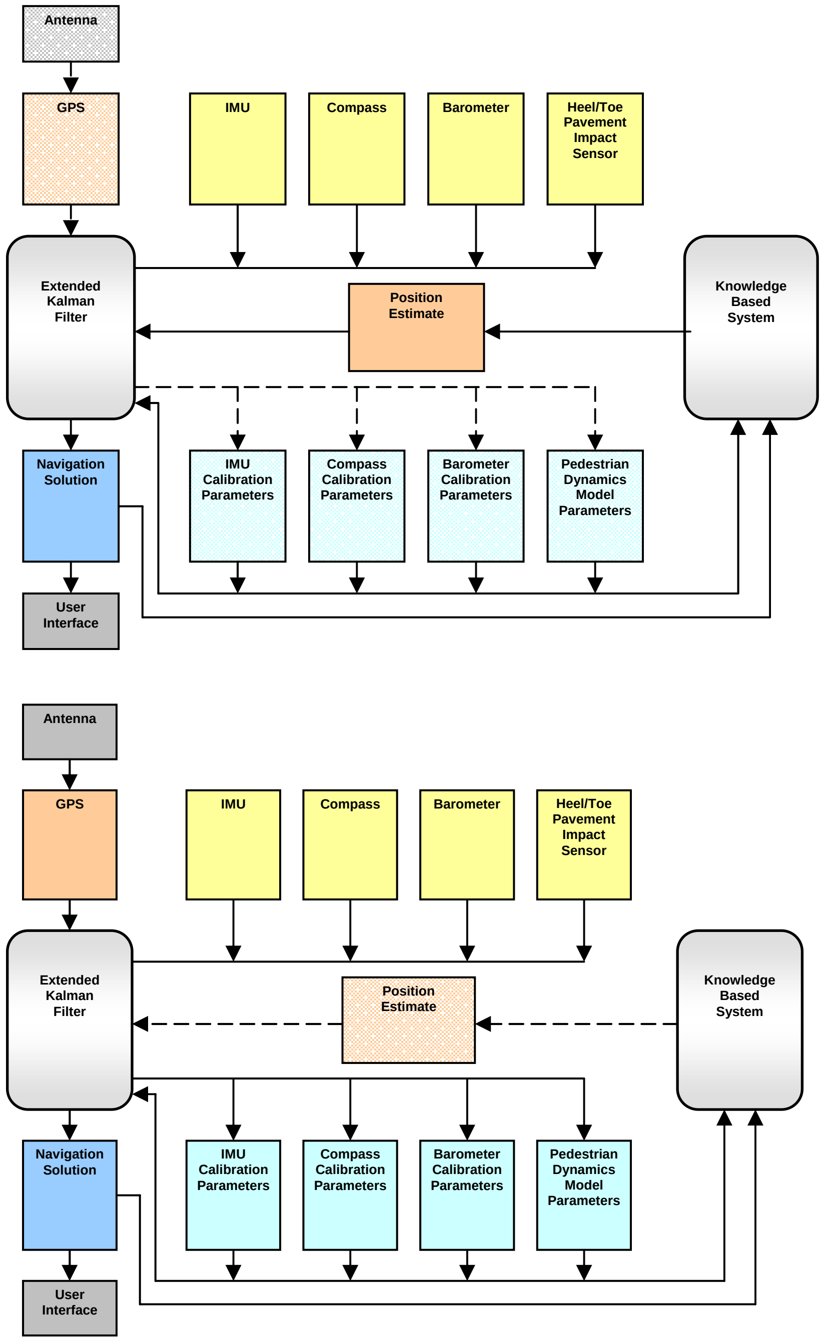

Figure 1. Personal navigator: system architecture; training mode (top) and dead reckoning mode (bottom) (Grejner-Brzezinska, *et al.*, 2007a).

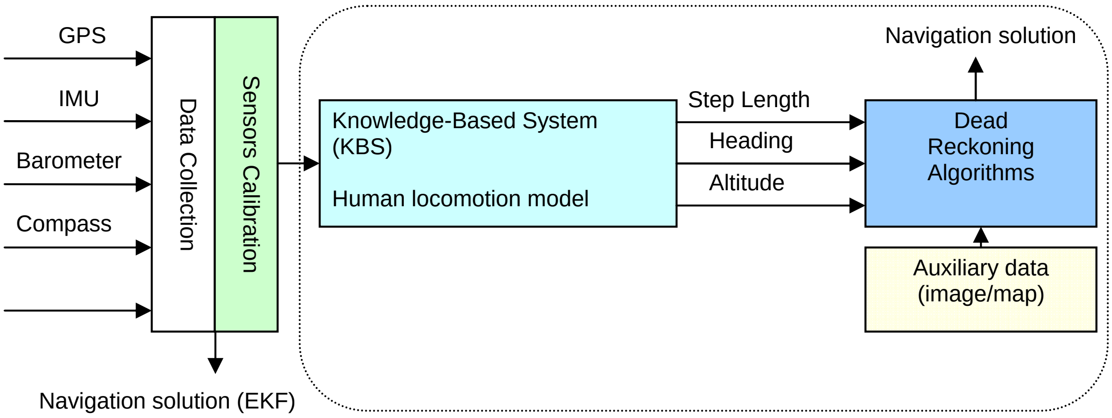

Figure 2. DR module of the personal navigator architecture.

Table 1 provides the sensor specifications in terms of stochastic modeling in the EKF architecture. Table 2 lists all sensors and their outputs with additional derived parameters that are currently used in the personal navigator (PN) prototype; they provide a continuous data stream to the KBS module during GPS outages. For more details on the filter design, hardware specification and current prototype implementation, see (Grejner-Brzezinska, *et al.*, 2007a and b, Toth *et al.*, 2007; Moafipoor *et al.*, 2007).

		Initial Covariance matrix	Statistical Model, White Noise
Position		100 m	RC, 0
Velocity		1 m/s	RW, 5 µg
Attitude	**Pitch, Roll**	1°	RW, 0.001 °/√hr
	Heading	2°	
Accelerometer Bias		1 mg	RW, 20 µg/ √hr
Accelerometer Scale Factor		120 ppm	RC, 0
Gyro Bias		1°/hr	RW, 0.125 °/√hr
Gyro Scale Factor		10 ppm	RC, 0

Table 1. HG1700 sensor specification (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.

In to facilitate DR navigation, at the minimum, operator's step length (SL), step frequency (SF) and heading information are needed. In this implementation, micro-switches, located in the shoe soles (heal and toes), synchronized with GPS time are used directly to sense the impact, i.e., the instances when operator's shoes hit the ground. These provide an instantaneous and accurate step frequency and step count measurements. With heading (azimuth, *Az*) measured by a magnetometer and/or IMU and known step frequency, as well as SL provided by the KBS system, DR can be accomplished as:

$$\Delta x = \sum_{k=1}^{n} SL_k \times \sin(Az_k) \qquad (1)$$

$$\Delta y = \sum_{k=1}^{n} SL_k \times \cos(Az_k) \qquad (2)$$

where Δx and Δy are the total distance traveled in the local X and Y direction, and n is the number of the steps.

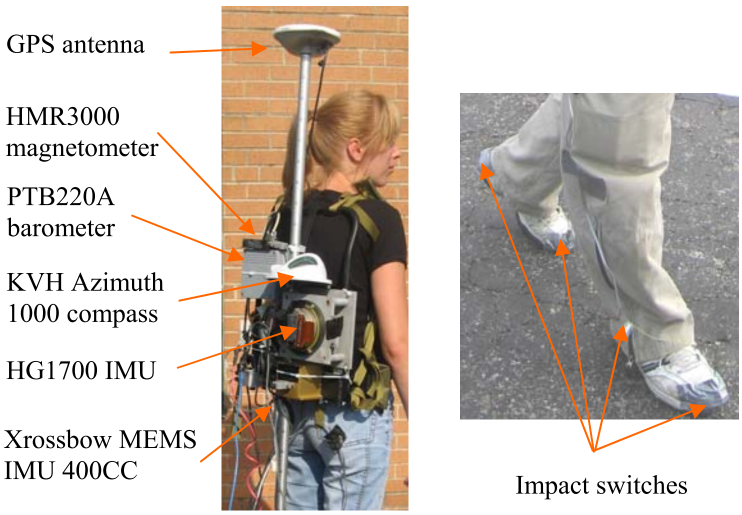

Figure 3. Sensor configuration in the current PN prototype.

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
Magnetometer/compass	- Angular rate - Heading
Barometer	- Var(Δh) - $\sum$($\|\Delta h\|$) - Altitude
Step sensors	- Step events
External data	- Person's height, age, weight

Table 2. Sensors and body locomotion parameterization.

2.2 Knowledge-Based System: Principles and Algorithmic Design

Currently, two separate architectures are implemented in the prototype of the Knowledge-Based System, (1) based on ANN, and (2) based on Fuzzy Logic (FL). They are currently stand alone modules, and no interaction between them is considered. The performance of both modules is currently under testing, and after this task has been completed, the final structure of KBS will be selected, depending on the test results. It is likely that some combination of both approaches will be selected; in addition, a control mechanism for switching between EKF and DR module will be implemented to assure a seamless transition between the GPS-driven and GPS-denied navigation environemnts. Even though the performance evaluation of the ANN-based system showed good results (Grejner-Brzezinska, *et al.*, 2007b, Toth *et al.*, 2007; Moafipoor *et al.*, 2007), ANN-based approach to SL modeling does not allow direct recognition of the locomotion pattern, and the quality of the output strongly depends on the training data sets. Moreover, the addition of constraints (e.g., hallway layout, digital map information) is very difficult. To that extent, the implementation based on Fuzzy Logic holds the promise of providing more process control, more flexibility and more transparency in the SL prediction process, as compared to the ANN-based solution. It is expected that the interpretation of operator's behavior will be possible with the FL-based implementation. Moreover, this approach should facilitate an relatively easy addition of constraints, such as, hallway layout for indoor navigation, or digital map information.

A very brief overview of the KBS implementations is given below, while for more details on both implementations the reader is referred to (Grejner-Brzezinska, *et al.*, 2007a and b, Toth *et al.*, 2007; Moafipoor *et al.*, 2007).

2.2.1. ANN-based knowledge-based system

The heart of the KBS is a single-layer artificial neural network with Gaussian function (G) selected as Radial Basis Function (RBF). A single-layer artificial neural network with RBF was selected as an alternative to a multilayer perceptron (MLP) since it is simpler to train, even though it typically needs more neurons than MLP (Principe *et al.*, 2000). In Figure 4, *n*, the number of RBF functions, ranges between 30 and 40 in a single hidden layer, and one output parameter, SL, is provided. The ANN learning rate was empirically selected as 0.05, and the total number of iterations is normally around 500. As shown in Figure 4, the current implementation of ANN takes up to six parameters: SF, total acceleration |a|, terrain slope, operator's height, peak-to-peak variation in acceleration, var(|a|), and total change in terrain elevation ($\sum \Delta h_{Baro}$). Since the input parameters are of different physical nature, the parameters are normalized to the same numeric range before they are fed to the ANN. When training an ANN, the rule of thumb is: use as input all variables that can be thought of as having problem-oriented relevance, but avoid unnecessarily large and inadequate ANN by preprocessing of input data (Lee and Mase, 2001). The preprocessing step can be thought of as, for example, a suitable transformation. Consequently, to remove any possible correlation from the input data, Principal Component Analysis (PCA) was performed on a larger training set. The results indicated medium parameter correlation; consequently, reducing the parameter space to only three components, corresponding to the three largest eigenvalues, achieved a near identical performance as compared to the case when all six parameters were used. For details on the PCA-based data preprocessing see (Grejner-Brzezinska *et al.*, 2006b and 2007a). Table 3 illustrates an example of the performance of the ANN-based KBS for SL modeling and DR trajectory reconstruction with and without PC transformation.

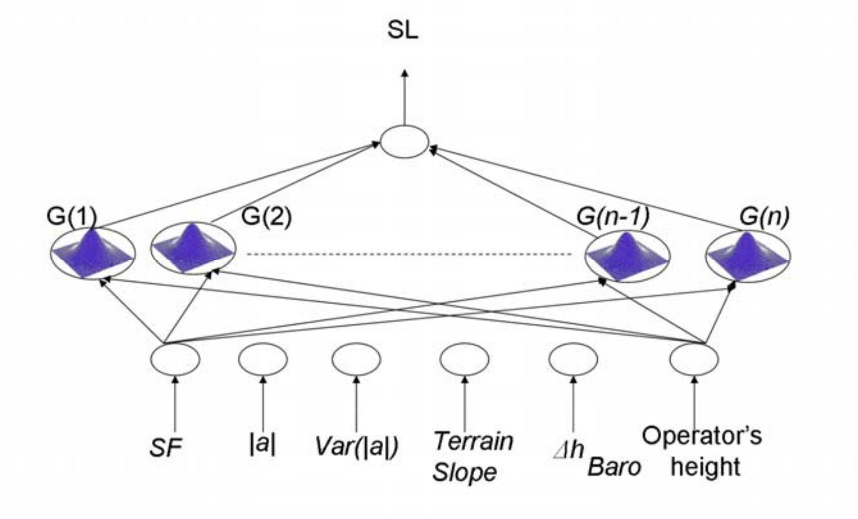

Figure 4. Conceptual design of the RBF-based ANN.

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

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 3. Statistical differences between the reference (known) SL and ANN-predicted SL (top) and the resulting DR navigation (bottom). No reduction of the parameter space applied. Loop of 355 m circumference traveled three times, two loops used for training, one for testing; reference heading used.

2.2.2. Fuzzy logic-based knowledge-based system

The principal elements in designing a FL system include: (1) defining input and output variables, (2) selecting the quantization level of the input and output space and the corresponding membership functions, (3) collecting knowledge representation in the form of fuzzy rules, and (4) designing the inference mechanism and defuzzification operators (see Figure 5). In the current design, six variables are used as inputs to the FL system for SL modeling; these are locomotion pattern, stride interval time and its variation, terrain slope, operator's height and trajectory curvature. The output of the system consists of two variables, whose combination represents the overall estimation of SL value for each pace. The first variable is the average size of SL determined partially by evaluating the locomotion pattern and the stride interval. The second variable is the variation of the SL, ΔSL, determined by the rest of the input variables. The main objective of such an output design is to approximate the SL function in more generic form, independent of the individual operator, but still close to the operating environments and other physical dynamic attributes. The details of the design and implementation of KBS based on Fuzzy Logic are presented in Moafipoor *et al.* (2007). A brief summary is presented below.

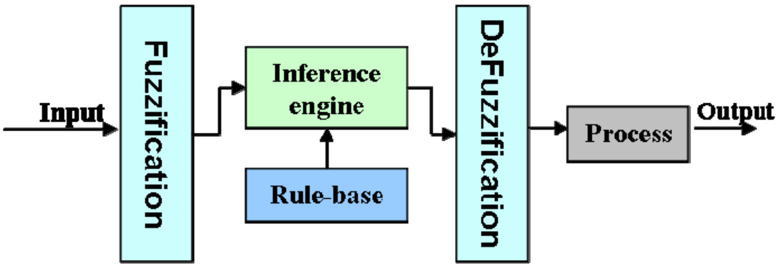

Figure 5. Fuzzy logic controller architecture (Kosko, 1991).

In general, fuzzy systems combine fuzzy sets with fuzzy rules to model and control complex non-linear behaviors. A fuzzy set, *A*, in a nonempty set, *X*, is defined by membership functions, η_A, interpreted as the degree of membership of each element, *x*, in the fuzzy set *A* over the unit interval:

$$A = \{x, \eta_A(x)\}, \quad \eta_A : x \to [0,1], \quad x \in X \qquad (3)$$

The value of the membership function indicates the degree of membership of a quantity *x* in the fuzzy set. If the membership value is 1, the quantity is perfectly representative of the set, and if it is 0, the quantity is not at all a member of the set. Membership functions are usually represented as parametric functions, such as triangle functions, trapezoidal functions, or bell-shaped functions (see Figure 6 for an example membership function and Table 4 for example of fuzzy rules for SL modeling and Figure 7 for a generic design of a Fuzzy System for SL modeling).

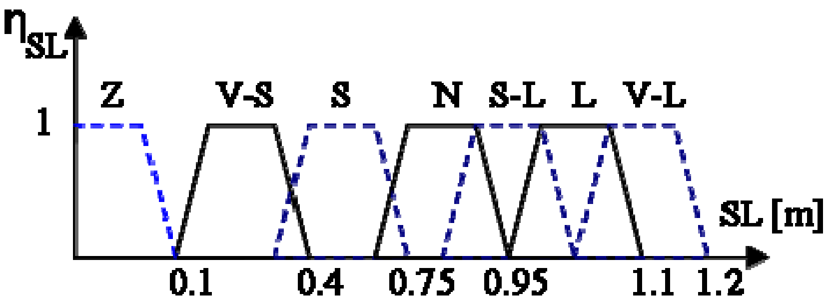

Figure 6. Membership function of SL; on the vertical axis, the membership degree indicates to what degree the value of SL is in a set. Based on expert knowledge seven quantization levels for SL estimation (the number of locomotion patterns) were defined, including zero (Z), very short (V-S), short (S), normal (N), semi-long (S-L) long (L), and very long (V-L), indicating the degree of membership of the average SL parameter to the corresponding fuzzy set.

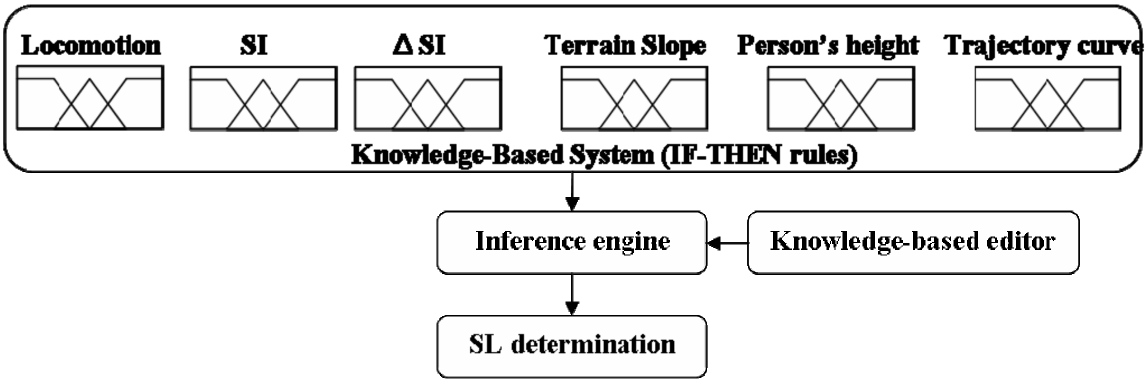

Figure 7. KBS for SL modeling based on Fuzzy Logic.

Antecedent	Consequent
SI is Normal or Activity is Walking	SL is Normal
ΔSI is Negative	ΔSL is Big Increase
ΔSI is Positive	ΔSL is Big Decrease
Activity is Walking and Path is Semi_Curve	ΔSL is Small Increase
Activity is Walking and Path is Curve	ΔSL is Small Decrease
SI is Slow and Activity is Crawling and Slope is Uphill and Operator's Height is Medium	ΔSL is Small Decrease
SI is Slow and Activity is Walking and Slope is Downhill and Operator's Height is Medium	ΔSL is Small Increase
SI is Semi-Fast and Activity is Walking and Slope is Level and Operator's Height is Medium	ΔSL is Small Decrease
SI is Semi-Fast and Activity is Running and Slope is Level and Operator's Height is Medium	ΔSL is Small Increase

Table 4. Fuzzy rules for SL modeling: IF Antecedent THEN Consequent.

3. PERFORMANCE EVALUATION OF KBS: ANN vs FUZZY LOGIC

The performance evaluation of the KBS has been documented in earlier publications (e.g., Grejner-Brzezinska *et al*., 2006b, 2007a and b) where test data were collected by multiple operators in the outdoor environment. In this section, the emphasis is on the most recent system testing performed predominantly indoors. For completeness, Table 5 provides typical performance statistics for the outdoor tests.

The test data were collected on August 21, 24, 26, 2007 in the one-story building of the Center for Mapping at the OSU Campus and in the neighboring parking lot. Two different operators, S and E, collected data both indoors and outdoors, and ANN and Fuzzy Logic KBS were used for SL modeling and subsequently for the DR trajectory computation. A 5 to10-minute initialization/calibration was performed outside the building in the form of two loops; then the operators were asked to return to the initialization point, collect data for a few static epochs, and proceed to the indoor data collection. After completing two indoor loops, operators returned to the starting point and collected again a few epochs of static data for reference. The indoor reference trajectory was established by classical surveying methods by measuring a set of reference points with cm-level accuracy (see Figure 8 for the test point layout). The differences between the reference and DR trajectories were analyzed as a measure of the DR navigation performance.

Test data set	SL modeling	Mean [m]	Std [m]	Max [m]	End Misclosure [m]	CEP(50%) [m]	CEP(95%) [m]
Loop 86 m	Fuzzy logic	0.67	0.21	0.95	0.91	0.60	0.90
	ANN	0.18	0.10	0.38	0.09	0.19	0.37
Loop 97m	Fuzzy logic	0.58	0.25	0.90	0.65	0.62	0.83
	ANN	0.40	0.11	0.62	0.97	0.43	0.53

Test data set	SL modeling	Mean [m]	Std [m]	Max [m]	End Misclosure [m]	CEP(50%) [m]	CEP(95%) [m]
Loop 86 m	Fuzzy logic	2.62	0.76	3.34	3.14	2.99	3.29
	ANN	2.09	0.84	3.07	2.25	2.20	3.00
Loop 97m	Fuzzy logic	1.87	0.47	2.86	2.36	1.87	2.57
	ANN	2.06	0.54	3.00	3.14	2.15	2.85

Table 5. Navigation performance assessment: outdoors: true heading used in DR mode (top); heading provided by calibrated HMR3000 magnetometer (bottom).

Tables 6-7 summarize the DR navigation results for both operators using FL- and ANN-based SL modeling and heading provided by the magnetometer (Table 6) and by the gyro (Table 7). As can be observed in the Tables, gyro heading provides substantially better results, as compared to the magnetometer heading. Both KBS implementation provide comparable results. More tests are needed in more complex environments, such as staircase and sloping terrain, before the architecture of the KBS module can be finalized (for preliminary results on sloping terrain see Grejner-Brzezinska *et al.*, 2007b).

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

Table 6. Indoor navigation performance assessment; HMR3000 magnetometer heading used in DR mode.

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

Table 7. Indoor navigation performance assessment; HG1700 gyro heading used in DR mode.

4. CONCLUSIONS

The prototype of human locomotion modeling (step length, SL) using ANN- and FL-based KBS to support personal navigation in DR mode during GPS signal outages or indoors was presented. Sample training and testing data were collected indoors and outdoors by different operators. The focus of the study presented here was on assessing the performance of the two approaches to KBS, namely ANN and FL. The results showed that CEP50 < 3m in positioning performance could be consistently achieved for the tested trajectories. Up to date testing revealed that outdoor DR trajectories up to 500 m and indoor trajectories up to 100 m provide navigation performance within the project specifications. More tests are still underway and additional algorithmic implementation follows, such as ZUPT utilization and appropriate heading modeling using ANN and/or FL.

ACKNOWLEDGEMENTS

This research is supported by the National Geospatial-Intelligence Agency 2004 NURI grant.

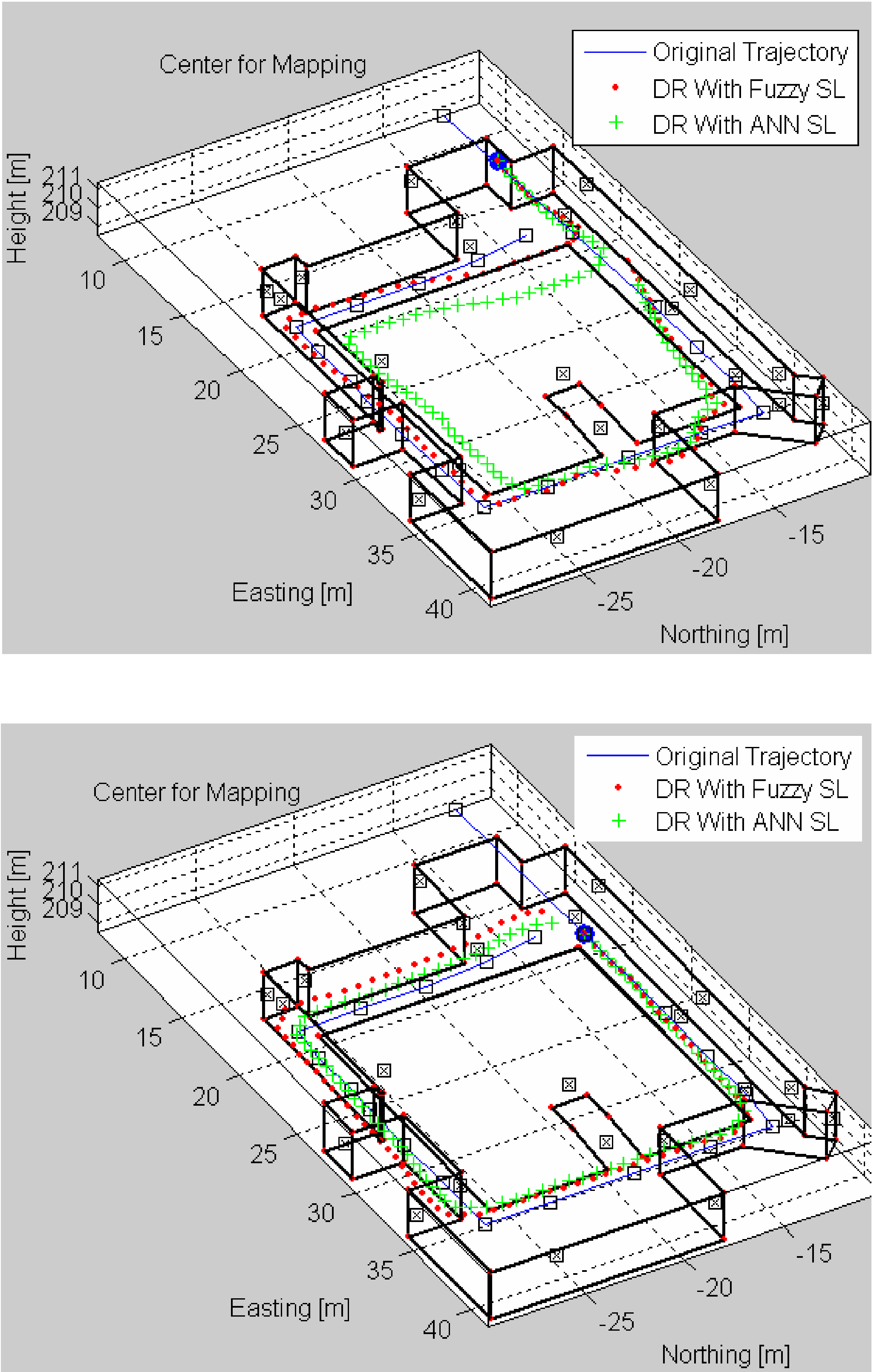

Figure 8. Indoor navigation: ANN and FL SL modeling, (top) augmented by magnetometer heading, operator S, (bottom) augmented by gyro heading, operator E. The squares indicate floor-placed reference points, the crosses denote the wall targets used for image referencing (not addressed here).

REFERENCES

Barnes JB, Rizos C, Wang J, Small D, Voight G, Gambale N (2003) High precision indoor and outdoor positioning using LocataNet. Proceedings 2003 Int. Symp. on GPS/GNSS, Tokyo, Japan, 15-18 November, pp. 9-18.

Grejner-Brzezinska DA, Toth CK, Jwa Y, Moafipoor S, Kwon JH (2006a) Seamless and reliable personal navigator, Proceedings ION National Technical Meeting, January 18-20, 2006, Monterey, California, USA, pp. 597-604.

Grejner-Brzezinska DA, Toth CK, Moafipoor S, and Jwa Y (2006b) 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, 2006, Baden, Austria, CD ROM.

Grejner-Brzezinska DA, Toth CK, Moafipoor S (2007a) Adaptive Knowledge-Based System for Personal Navigation in GPS-Denied Environments. Proceedings ION National Technical Meeting, San Diego, CA, January 22-24, 2007a, CD ROM.

Grejner-Brzezinska DA, Toth CK, Moafipoor S (2007a) Pedestrian tracking and navigation using adaptive knowledge system based on neural networks. *Journal of Applied Geodesy*, in press.

Kee C, Jun H, Yun D, Kim B, Kim Y, Parkinson B, Lenganstein T, Pullen S, and Lee J (2000) Development of Indoor Navigation System using Asynchronous Pseudolite. Proceedings of ION GPS-2000, Salt Lake, Utah, USA, September, 2000, 1038–1045.

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), 1310-1321.

Lachapelle G, Godha S and Cannon ME (2006) Performance of Integrated HSGPS-IMU Technology for Pedestrian Navigation under Signal Masking. Proceeding of European Navigation Conference, Manchester, U.K., 8-10 May, Royal Institute of Navigation, 24 pages.

Soon BHK, Poh EK, Barnes JB, Lee H.K., Zhang J, Lee HK, Rizos C (2003) Preliminary results of the carrier-smoothed code-phase differential GPS/pseudolite system. Proceeding 6th Int. Symp. on Satellite Navigation Technology Including Mobile Positioning & Location Services, Melbourne, Australia, 22-25 July, CD-ROM, paper 48.

Toth CK, Grejner-Brzezinska DA, Moafipoor S (2007) Pedestrian Tracking and Navigation Using Neural Networks and Fuzzy Logic. Proceedings IEEE International Symposium on Intelligent Signal Processing 3-5 October 2007, Alcala de Henares (Madrid) Spain, 657-662.