DESIGN AND CALIBRATION OF A NEURAL NETWORK-BASED ADAPTIVE KNOWLEDGE SYSTEM FOR MULTI-SENSOR PERSONAL NAVIGATION

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ABSTRACT:

This paper presents the current design and the preliminary 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 main purpose of this research project is to develop theoretical foundations and implementation algorithms, which integrate the Global Positioning System (GPS), Micro-electro-mechanical inertial measurement unit (MEMS IMU), digital barometer and compass to provide seamless position information facilitating navigation and tracking of the military and rescue ground personnel. The system model represents an open-ended architecture, which will be able to incorporate additional navigation and imaging sensor data in the future, extending the system operations to confined and indoor environments. In addition, the current system architecture is designed to incorporate a simplified dynamic model of human locomotion used for navigation in dead reckoning (DR) mode. The adaptive knowledge system, based on the Artificial Neural Networks (ANN), is designed to support this functionality. The system is trained during the GPS signal reception and is subsequently used to support navigation under GPS-denied conditions. The stride parameters, step frequency (SF) and step length (SL) are extracted from GPS data (SF) and GPS-timed impact switches (SF) during the system calibration period. SF is correlated with several data types, such as acceleration, acceleration variation, SF, terrain slope, etc., which are extracted from other non-GPS sensors and constitute the input parameters to ANN that predicts SL during the GPS signal blockage. The predicted SL, together with the heading information from the compass and gyro, support the DR navigation. The current target accuracy of the system is 3-5 m CEP (circular error probable). This paper focuses on the design architecture of the integrated system and the preliminary performance analysis, with a special emphasis on DR navigation supported by the human locomotion model.

1. INTRODUCTION

The recent technological advances in positioning and tracking sensors, including the Global Positioning System (GPS), MEMS IMU (micro-electromechanical systems; inertial measurement unit), digital compass and digital barometer/altimeter offer a potential to develop small and portable systems for navigation and decision support for military and rescue ground personnel. The ongoing GPS modernization program, advances in the high-sensitivity receiver technology, capable of supporting navigation indoor andin confined environments (Lachapelle et al., 2006) well-established MEMS accelerometer technology, and steadily improving MEMS gyro technology, with the target of achieving 1°/h gyro stability in the next few years, as well as availability of other RF signals capable of supporting navigation, such as, wireless local area network (WLAN) or Bluetooth (that can facilitate wireless connection among the sensors used for navigation) etc., enable efficient integration of these sensors as the primary technology components for personal navigation. It should be noted that personal navigation has been of research interest for a number of years years; two different approaches within the scope of pedestrian navigation can be distinguished, namely, (1) multi-sensor sensor integration (e.g., Anderson et al., 2001; Retscher and Thienelt, 2004; Kourogi et al., 2006) and (2) pedometry (e.g., Beauregard and Haas, 2006). The next logical step is to integrate these two approaches to form an intelligent navigation system, where the term intelligent navigation represents the transition from the conventional GPS/IMU-based systems to multi-sensor systems that increasingly rely on integrating knowledge-based systems, including artificial neural networks (ANN), Fuzzy Logic, etc. to accommodate human locomotion modeling for pedometry. Furthermore, the application of navigation technologies that are driven by the availability of GPS is transitioning from the typical open sky environment to the indoor and confined environments, such as urban and underground settings. In this evolution, a variety of new sensors, such as electronic compasses, barometers, motion sensors, RF signals of opportunity, GIS/CAD map data, etc. are introduced. Consequently, with the proliferation of various signal processing techniques and dynamic system modeling that are introduced to achieve more robust navigation solutions, the traditional Extended Kalman Filter (EKF) approach to multi-sensory data integration becomes more complex in order to accommodate new and often non-linear data and dynamic models. Furthermore, knowledge-based systems are needed to handle the complexity of a wide range of data entities as well as their rapidly changing availability in varying environments. The knowledge-based systems can work in a variety of ways, such as individual agents monitoring input signals conditions and controlling the EKF with adaptive error models or even replacing the EKF with an alternative solution.

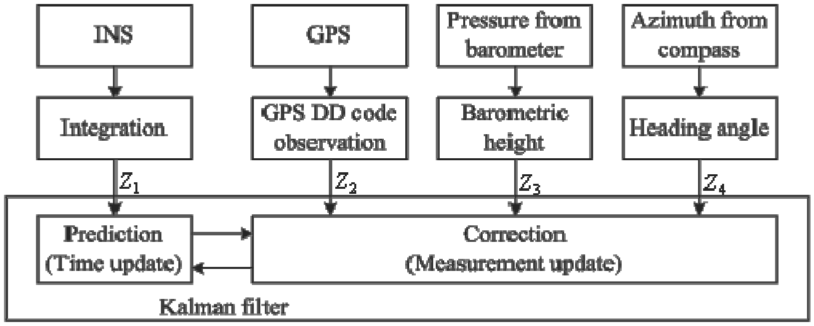

Figure 1: Conceptual design of the integrated filter, Z_i (i = 1, 2, 3, 4) indicate multi-senor measurements supported by multi-agent processes that control the respective sensors/processes in the integrated system.

As a result, non-linear Bayesian Filters, such as Unscented Kalman Filter (UKF) and Particle Filter (PF) are being used (see, for example, Julier and Uhlmann, 1997; Wan and van der Merwe, 2001; Liu and Chen, 1998; Wan et al., 2000; Ristic et al., 2004; Yi and Grejner-Brzezinska, 2005a, 2006a-b), and non-traditional approaches to sensor integration and modeling, such as Artificial Neural Networks (Kaygisiz et al., 2003; Chiang et al., 2003; Wang et al., 2006; Grejner-Brzezinska et al., 2006 and 2007), and Fuzzy Logic (e.g., Simon, 2003; Abdel-Hamid et al., 2005) are being introduced to navigation algorithms.

This paper presents a design, prototype implementation and performance analysis of a personal navigator based on multi-sensor integration, augmented by the human locomotion model that supports navigation during GPS gaps. The accuracy requirement is considered at 3-5 m CEP (circular error probable) level. At the current stage of the research, the algorithmic concept of the GPS-based, MEMS IMU-augmented personal navigator system with an open-ended architecture has been implemented. In the present system design and implementation, the following sensors are integrated in the tightly coupled EKF: GPS carrier phase and pseudorange measurements in the double difference (DD) mode, Honeywell HG1700 IMU (note that Crossbow MEMS IMU 400CC implemented initially does not meet the accuracy specifications for this project, based on the initial performance tests), PTB220A barometer and Azimuth 1000 digital compass; the most recent extension to the prototype is a 3-axis magnetometer that is replacing the Azimuth 1000 compass that has not met the performance requirements for this project.

The performance analysis presented here is focused on (1) sensor calibration and (2) navigation during the loss of GPS signals. As already mentioned, the system architecture is designed to incorporate a dynamic model of human locomotion. The system is trained during the GPS signal acquisition using Radial Basis Function (RBF) neural network model with up to six input parameters that contain information about the step length (SL), such as, step frequency (SF), mean acceleration (|a|), variance of acceleration (Var|a|), terrain slope, barometric height variation, and operator's height. The calibrated model of stride parameters (SL and SF), provided by the ANN-based adaptive knowledge system, and heading information from the compass/IMU facilitate dead reckoning (DR) navigation during the GPS gaps.

2. THE CURRENT SYSTEM PROTOTYPE

The conceptual design of the current system is illustrated in Figure 1. The primary four sensors, GPS, IMU, barometer, and compass are integrated in a tightly coupled EKF, where GPS carrier phase and/or pseudorange data are used in the double-difference mode to obtain a full navigation solution, as well as the IMU and other sensor errors. This design is based on the GPS/IMU system, AIMS™, developed earlier at the Ohio State University (e.g., Grejner-Brzezinska and Wang, 1998; Grejner-Brzezinska, 1999; Toth and Brzezinska, 1998), with the barometer and compass introduced to aid the height and heading estimation, respectively, when GPS signals are blocked. These sensors are continuously calibrated during the GPS signal availability. Naturally, if the IMU is of low quality, a more accurate compass (e.g., 0.5-1° heading accuracy) may contribute to calibrating and aiding the IMU-based heading.

In sensor fusion, it is of special importance to assess the proper stochastic error models for each sensor. Table 1 shows the stochastic error models used in the current system implementation. The error models may be updated in the future, based on the additional performance tests and the actual characteristics of each sensor. Currently, the sensors used in the prototype are: dual frequency GPS receiver (Novatel OEM-4), tactical grade IMU HG1700 (optionally, MEMS IMU400C, see the earlier note on that subject), PTB220A barometer, and KVH Azimuth 1000 digital compass.

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 constant
	Scale factor	Random walk
Digital Compass	Bias	Random constant
	Scale factor	Random walk

Table 1: Stochastic error models for the multi-sensor personal navigation system.

Figure 2 illustrates the current design of the integrated filter and the corresponding ANN-based adaptive knowledge system that models the human dynamics. The dashed line between the "adaptive knowledge base" and the "position estimate" windows in the figure indicates that during the GPS signal presence, the human dynamics (i.e., SL and SF) are modeled, while during the signal blockage this line becomes solid, meaning that the adaptive knowledge system contributes to position estimation in that scenario.

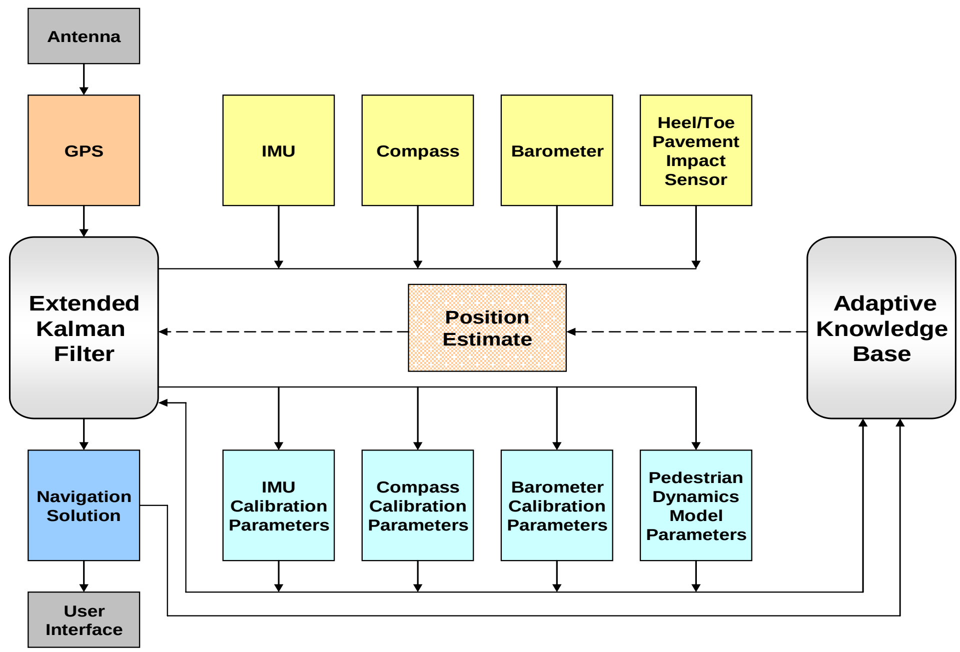

Figure 2: Conceptual design of the integrated filter and the adaptive knowledge system (shown in the calibration mode).

3. PRELIMINARY PERFORMANCE ANALYSIS

The preliminary performance analyses were carried out using the simulated data. Subsequently, several kinematic tests, in the controlled environment, were performed at The Ohio State University campus in July and November 2005 and June 2006, where GPS, IMU, compass and barometer data were collected. Some of these data sets, as well as the simulated data are used in the performance analyses presented in this paper. Namely, the first part of the analysis discussed here is based on simulations, where the synthetic data were created to determine if the specs for the preliminary hardware selection would indeed meet the project accuracy requirements. The actual data collected for this test were: dual frequency GPS and LN100 (navigation grade IMU; 0.8 nmi/h CEP, gyro bias – 0.003°/h, accelerometer bias – 25μg), while all the other sensor data (i.e., barometer, compass, consumer-grade MEMS, and tactical grade IMU) were simulated using the manufacturer specifications of their (average) error characteristics.

3.1 Positioning accuracy of the integrated sensor suite: GPS/IMU/compass/ barometer simulations

One of the research questions that is addressed here is: can the pseudorange measurements be used instead of the carrier phase measurements to assure the target positional accuracy? To assess the accuracy achievable with pseudorange data, the pseudorange/MEMS IMU (simulated) positioning results were compared with the reference solution, i.e., the carrier phase/LN100 (actual data) and subsequently, simulated compass and barometer data were added to the pseudorange/MEMS IMU to test their impact on the navigation solutions. Table 2 shows the summary statistics of these tests in terms of the mean and the standard deviation of the differences between the two simulations and the reference solution; the solution based on pseudorange/MEMS IMU is denoted as solution 1, and the pseudorange/MEMS IMU/compass/barometer model represent solution 2. The duration of the test was about 800 seconds. The LN100/carrier phase reference solution was obtained with the AIMS™ system (see, for example, Toth and Grejner-Brzezinska, 1998; Grejner Brzezinska, 1999); its positional accuracy was at the level of a few centimeters per coordinate.

	Reference solution 1		Reference solution 2	
	Mean	**STD**	**Mean**	**STD**
N [m]	0.66	0.54	0.58	0. 50
E [m]	0.80	0.69	0.72	0.58
U [m]	0.93	0.71	0.80	0.53
Roll [°]	1.38	0.95	1.36	1.00
Pitch [°]	1.47	0.96	1.00	0.78
Heading [°]	10.68	8.46	1.05	0.78

Table 2: Navigation accuracy of the pseudorange/MEMS IMU (solution 1) and the pseudorange/MEMS IMU/compass/barometer model (solution 2) with respect to the reference solution (DD carrier phase/LN100).

As can be observed, the barometer has some impact on the height accuracy, but the most pronounced improvement is evident in heading, as a result of including the compass measurements, since MEMS IMU simulated here was of very low quality (1°/s gyro drift).

Solution type		No GPS gap				GPS gap of 550 s			
		HG1700/CP		HG1700/PR		HG1700/CP		HG1700/PR	
		Mean, std	Diff.	Mean, std	Diff.	Mean, std	Diff.	Mean, std	Diff.
Heading [º]	GPS/INS	0.45±1.01	0.6	0.48±1.08	0.6	-1.02±3.64	3.3	1.85±3.49	3.8
	GPS/INS/B/C	0.45±1.01	0.6	0.42±1.06	0.7	1.03±3.63	3.3	1.79±3.50	3.7
Height [m]	GPS/INS	-0.05±0.35	0.1	-0.52±0.88	0.4	-46.5±63.0	210	-134±179	620
	GPS/INS/B/C	-0.02±0.35	0.1	-0.27±0.77	0.2	-1.13±2.16	0.8	-1.85±2.25	0.3

Table 3: The impact of barometer (B) and compass (C) on the navigation solution accuracy; CP denotes double differenced carrier phase data; PR denotes pseudorange data; Diff denotes the difference between the reference solution and the tested solution.

3.2 Positioning accuracy of the integrated sensor suite: GPS/IMU/compass/ barometer kinematic data

Table 3 illustrates an example of the navigation performance improvement when a tactical-grade HG1700 sensor (performance equivalent to the assumed future MEMS IMU) is used instead of the MEMS IMU tested in Section 3.1; the kinematic data were collected on June 29, 2006. Clearly, HG1700 supported by pseudorange data and compass/barometer information provides the navigation performance well within the required accuracy specifications, when GPS data are available. It should be noted that the compass and the barometer do not have, as expected, any significant impact on the navigation solution when GPS signals are available. The ultimate test, however, is the system's performance during GPS gaps. To address that, Table 3 also provides the accuracy statistics of an example free-inertial navigation where (1) only HG1700 was used and (2) barometer and compass were added. The system was calibrated for ~350 s before the GPS gap was introduced. The reference solution was based on LN100 data combined with double differenced carrier phase data. It should be noted that the trajectory of this test was subject to mild dynamics; therefore the compass provided good quality heading (within the compass performance specs) during the GPS drop-outs. The KVH Azimuth 1000 digital compass does not perform well under higher dynamics, most probably due to internal signal smoothing (the heading change does not reflect the actual dynamics of the trajectory, and a several-second delay in showing the actual heading has been observed).

4. NAVIGATION SUPPORTED BY HUMAN DYNAMICS MODEL

In a number of previously published research results, GPS was used to determine the stride frequency and interval by analyzing the spectrum of the acceleration provided by an IMU (e.g., Hausdorff et al., 2001; Brand and Phillips, 2003; Cho et al., 2003). This can, however, be a tedious process, requiring extensive testing for the threshold selection on a case-by-case basis. Therefore, in this research, an additional sensor, an impact (contact) switch, is added to directly measure the events of foot-to-ground impact, synchronized to the GPS time. The impact switches are placed in the heels and toes of the operator's shoes, and provide a timed impulse during the impact with the ground, allowing for instantaneous estimation of the gait cycle.

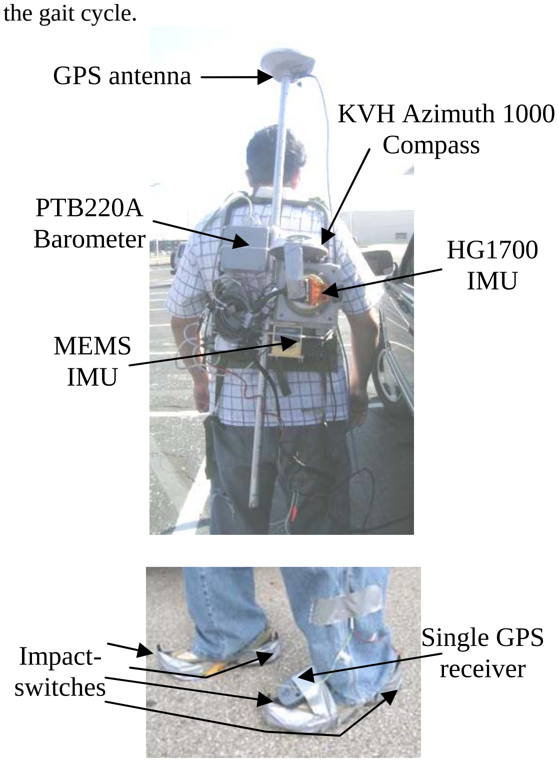

Figure 3: Test sensor configuration.

In general, a known (pre-calibrated) human locomotion model can be used to support navigation during GPS gap. This means that the step frequency (provided by the impact switches) and the step length provided by the calibrated knowledge-based system, and the heading information from the compass/IMU should be available. The knowledge-based system must be trained during the presence of GPS signal, as already explained, and the training must be customized for a particular user/operator; in addition, different motion patterns and different environmental impacts must also be considered during the training process. Therefore, a learning mechanism, generally outside the positioning filter, must be designed and implemented to assure a proper calibration/training procedure that would support reliable navigation without GPS, as shown in Figure 2.

It should be mentioned that sensor configuration and location on the user's body are also important factors, and cannot be overlooked in the calibration/performance assessment procedure. In the results presented here, based on the dataset collected in September 2005, a backpack configuration was used, as shown in Figure 3.

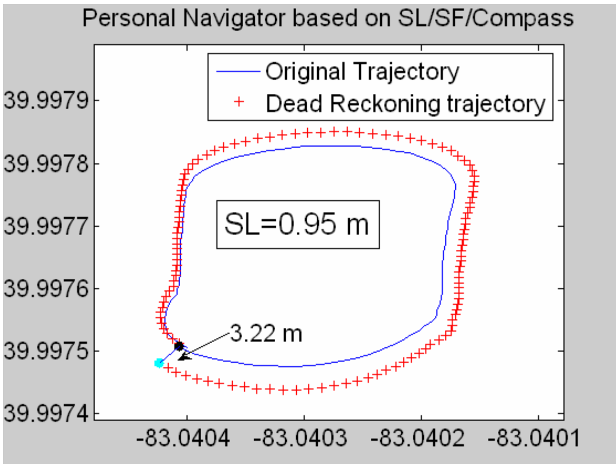

Figure 4: Reference and predicted trajectories; prediction is based on calibrated compass and SL/SF data.

The step length, defined here as the distance between the left and right heel impact sensors was extracted for a specific user moving on a flat circular path, as shown in Figure 4 (three repetitions of the same circular motion pattern were used here). The double difference carrier phase data were used to calibrate the step length based on the events measured by the impact switches. In order to test the step calibration results, GPS signal was turned off for one loop, and the navigation was performed using the compass heading (calibrated during the previous loop), the step size presented in Table 4 (loop 2), rescaled to 1/second sampling, and the SF sensed by the impact switches.

Step Length	Operator A	
	Mean [m]	Std [m]
Loop 1	0.61	0.05
Loop 2	0.63	0.04
Loop 3	0.72	0.10

Table 4: Mean and STD of the step length determined from three trials for the same operator; operator moved faster with higher SF in loop 3.

The navigation results compared to the correct (GPS) trajectory are presented in Figure 4. The final closure in the end of the loop is 3.22 m, which is well within the required accuracy specifications. Note that in this case, scale and bias, instead of a single bias only, were estimated for the compass calibration, to improve the calibration performance, as compared to the simulated case presented in section 3. More tests and analyses are currently being performed. The next step in this investigation is to test the calibration procedure along the trajectory with a varying terrain slope. Note that this test did not use the ANN-based adaptive knowledge system, but an average SL estimated from two previous well-defined trajectories completed by the same operator.

4.1 SL prediction using ANN

The implementation of the ANN-based knowledge system allows for more automated SL modeling, as compared to the simple training/testing scheme presented in the example above. A training/testing example is presented next. Also, to demonstrate the positive impact of the ANN input parameter preprocessing using the Principal Component Analysis (PCA) transform, Table 5 shows the results of the SL modeling without PCA transformation, and Table 6 shows a comparison of the 4-parameter case from Table 5 (last row) where PCA was applied. Notice a significant bias in the predicted SL during the performance testing for the case of no PCA, and a considerable improvement in training and performance checking for the case where the input parameters were PCA-transformed. Note that two loops of the circular path repeated by the operator were used for training and one loop was used for testing the knowledge-based system performance (the operator and trajectories were the same as used in the earlier example, as shown in Figure 4 and Table 4).

SL Modeling (No PCA)	Training [cm] mean ± std	Testing [cm] mean ± std
SF, |a|	3.6 ± 6.4	7.4 ± 8.4
SF, Var(|a|)	3.2 ± 5.7	6.8 ± 7.1
SF, |a|, Var(|a|), Slope	2.3 ± 4.9	7.1 ± 5

Table 5: ANN training and testing results, no PCA transformation applied to input parameters.

SL Modeling (With PCA)	Training [cm] mean ± std	Testing [cm] mean ± std
SF, |a|, Var(|a|), Slope	0 ± 0.3	1.5 ± 1.7

Table 6: Effect of PCA transformation on ANN training and testing; no reduction of the parameter space applied.

To further test the performance of the knowledge-based system in DR navigation mode, the results listed in Table 6 were used to predict the operator's trajectory. The reference trajectory, with the total distance of about 355m, was generated using GPS/IMU data. Figure 5 illustrates the comparison of the reference trajectory (blue), the trajectory generated using the ANN SL prediction, where the input parameters were not PCA-transformed (green), and where the input parameters were PCA-transformed (red). The mean and the standard deviation for the green trajectory with respect to the reference blue trajectory was 1.63 m ± 0.76 m; for the red trajectory the numbers were 0.89 m ± 0.28 m; the total end misclosure for the green and red trajectories were 1.6 m and 1.1 m, respectively, and the maximum departure from the reference of 3.08 m and 1.68 m, were observed for the green and red trajectories, respectively. The positive impact of decorrelating input parameters with the PCA transformation before passing them to ANN is clearly visible. Also, the method of SL calibration using the adaptive knowledge system described here shows a performance superior to the SL modeling based on the average SL observed for the training period, presented first.

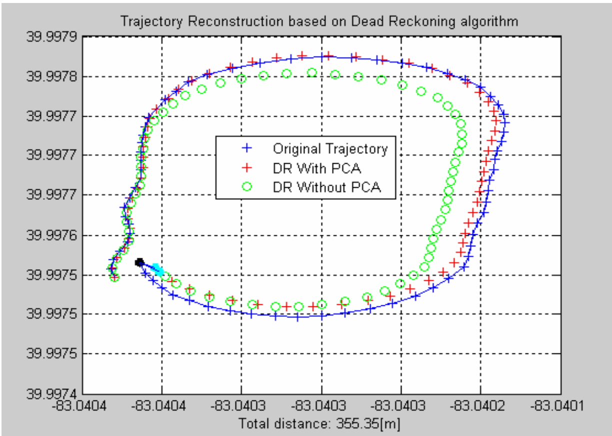

Figure 5: Comparison of the reference trajectory (blue), trajectory generated using the ANN where the input parameters were not PCA-transformed (green), and where the input parameters were PCA-transformed (red).

5. SUMMARY AND CONCLUSIONS

The design and the prototype implementation of a multi-sensor personal navigator were presented. The simulation-based performance analysis for the IMU, digital compass and barometer was discussed first, and the performance of multi-sensor navigation was tested in an actual kinematic scenario, with a special emphasis on the impact of the barometer and compass data during GPS signal outages. The accuracy of the navigation supported by the pre-calibrated human dynamics model was also discussed.

The preliminary results are encouraging; however, the MEMS IMU 400CC may not be a desirable sensor, as its gyro drifts very fast, and may not be able to provide the required accuracy and stability to the orientation solution. More detailed study of this sensor is presented in Grejner-Brzezinska et al. (2005) and Yi et al., (2005b). A tactical-grade HG1700 recently replaced the MEMS IMU in the current system prototype. Also, the digital compass used here may not be an optimal solution due to its significant internal smoothing and low gimbal range; this sensor has been recently replaced by a 3-axis magnetometer (Honeywell HR3000), and the system performance testing continues.

The human dynamics-supported navigation, tested with real kinematic data, especially with the impact switches that we introduced to detect the step events, is very promising. With this solution, no spectral analysis of the acceleration is needed to detect the step frequency. The PCA transformation introduced to decorrelate the ANN input parameters substantially improved the SL calibration; consequently, the navigation results obtained using the SL modeled with the PCA-transformed input parameters provides a superior performance to the case where no PCA transform is used. More tests are currently carried out to test the accuracy of DR navigation for varying step length along the trajectory and for more complicated trajectories with varying slope.

A full integration of human dynamics into the multi-sensor and multi-agent system is the next big challenge in this research effort. ANN and Fuzzy Logic are being currently considered to form the Fuzzy EKF architecture.

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