An Adaptive Multi-Sensor Positioning System for Personal Navigation

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BIOGRAPHIES

Dr. Heidi Kuusniemi received her M.Sc. degree in 2002 and D.Sc. (Tech.) degree in 2005 from Tampere University of Technology, Finland. Her doctoral studies on personal satellite navigation were partly conducted at the Department of Geomatics Engineering at the University of Calgary, Canada. After working as a GPS Software Engineer at Fastrax Ltd from 2005 to 2009, she joined the Department of Navigation and Positioning at the Finnish Geodetic Institute in May 2009 as a specialist research scientist with research interests covering various aspects of GNSS and sensor fusion for seamless outdoor/indoor positioning.

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Dr. Jingbin Liu is a senior research scientist in the Department of Navigation and Positioning at the Finnish Geodetic Institute. Prior to joining FGI, he worked for more than four years as a GPS receiver firmware engineer at SiRF (formerly Centrality) technology Inc. He received his M.Sc. and Ph.D degrees in geodesy in 2004 and 2008 and his bachelor degree in geodetic engineering in 2001 from Wuhan University, China. His research interests cover various aspects of outdoor/indoor seamless navigation, including GNSS precise positioning, integrated GNSS/inertial sensor positioning, indoor location awareness based on wireless signals, software defined GNSS receiver technology, and as well as GNSS-based meteorology.

Dr. Yuwei Chen received his B.S. from Electronics Engineering Department of Zhejiang University (China 1999) and M.E. from Information and Electronic Department of Zhejiang University (China 2002) and Ph.D in Circuit and System from Shanghai Institute of Technical Physics (SITP), Chinese Academy of Science (China 2005), respectively. He is now working at the Finnish Geodetic Institute as a specialist researcher in the Department of Navigation and Positioning. He has authored over 20 scientific papers on personal navigation and remote sensing and holds 5 patents (1 under application).

Dr. Ling Pei received his Ph.D degree in test measurement technology and instruments from the Southeast University, China, in 2007, joining the Finnish Geodetic Institute (FGI) at the same year. He is a senior research scientist in the Navigation and Positioning Department at FGI, where his research interests include indoor/outdoor seamless positioning, mobile computing, wireless positioning, and location-based services.

Wei Chen received his B.S. degree from the Department of Electronic Science and Technology, University of Science and Technology of China, Hefei, in 2005, and afterwards is a Ph.D candidate in the same department. He is a visiting student at the Finnish Geodetic Institute since September 2008. His research interests include seamless outdoor/indoor pedestrian navigation based on self-contained systems, and dead-reckoning sensors' calibration algorithms.

ABSTRACT

MEMS sensors, such as accelerometers, gyros and barometers are being widely suggested for augmentation to Global Navigation Satellite Systems (GNSS). Combining such sensor provided information loosely to GNSS positioning is, nevertheless, very demanding and plenty of adaptability is needed in order to obtain sufficient positioning accuracy and acceptable service availability. This paper presents a low-cost multi-sensor positioning system that includes a high-degree of adaptability; environment detection for adaptive filter coefficient steering and measurement rejection. The system analyzed includes a commercial GPS receiver, a 3-axis accelerometer, and a 2-axis digital compass; and the measurements from the different sources are combined in a central Kalman filter. Test results are presented of the adaptive system and the shown performance demonstrates the usefulness of the adaptive low-cost multi-sensor usage

with respect to a standalone high-sensitivity GPS solution.

INTRODUCTION

Navigation applications are becoming standard features in more and more commercially available devices. Locating a mobile user is however still a very challenging task, especially in GNSS degraded areas such as urban canyons and indoors. A seamless indoor/outdoor positioning solution requires utilizing additional technologies in parallel to satellite navigation due to satellite signals being often unattainable in for example deep indoors, or the high noise levels of the satellite signals available are causing significant degradation in the positioning performance.

Micro Electro Mechanical System (MEMS) sensors, such as accelerometers, gyros and barometers are being widely suggested for augmentation to GNSS for personal navigation, see e.g. [9-12]. Combining such sensor provided information loosely to GNSS positioning is, nevertheless, very demanding and plenty of adaptability as well as sensor measurement calibration algorithms are needed in order to obtain sufficient positioning accuracy and acceptable service availability.

Difficult signal environments of most mobile applications typically contain significant sources of disturbance. In poor signal areas, GNSS signals have typically greater noise levels and the measurements are affected by multipath propagation, echo-only signal reception, and even signal cross-correlation problems. The measurements from self-contained sensors, e.g. a digital compass, can also be significantly disturbed by any object bearing magnetic perturbation, for example an elevator. In addition, the sensors must be properly calibrated, and, any errors in the calibration procedure naturally affect the positioning performance. Therefore, outlier monitoring, adaptability, and error detection are essential. In addition, environment awareness is crucial when adapting filter coefficients, dynamic parameters, and outlier rejection limits according to location and application.

This paper presents a low-cost, "reduced" multi-sensor positioning system that includes a high-degree of adaptability; environment detection for adaptive filter coefficient steering and measurement rejection. The system analyzed includes a commercial GPS receiver, a 3-axis accelerometer, and a 2-axis digital compass, and the measurements from the different sources are combined in a central Kalman filter. The system is denoted as being a "reduced" multi-sensor approach because it is a gyro-free implementation. Test results are presented of the adaptive system and the shown performance demonstrates the usefulness of the adaptive multi-sensor usage with respect to a standalone high-sensitivity GPS solution for pedestrian applications.

MULTI-SENSOR POSITIONING PLATFORM

A multi-sensor positioning (MSP) approach is being under development at the Finnish Geodetic Institute (FGI) for pedestrian navigation purposes. The objective of our research is to achieve a seamless indoor-to-outdoor locating solution. The application environment of the platform under development is an advanced visitor demonstration scenario for the Shanghai World Exposition in 2010 [5, 6, 7, 13].

The hardware platform consists currently of a GPS receiver (Fastrax iTrax03), a digital signal processor (DSP), a 3D accelerometer (VTI SCA3000-D1), and a 2D digital compass (Honeywell HMC6352), as shown in Figures 1 and 2. In fact, the DSP is embedded in the GPS module. All the sensors are integrated into the DSP that hosts core software for real-time sensor data acquisition and real-time processing and position computation to estimate user's location, speed and direction.

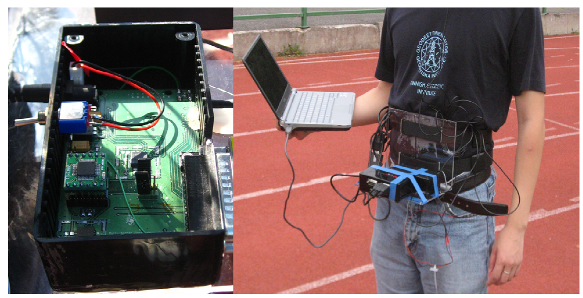

Figure 1. Multi-sensor positioning (MSP) platform for pedestrians including a GPS receiver, an accelerometer, and a digital compass.

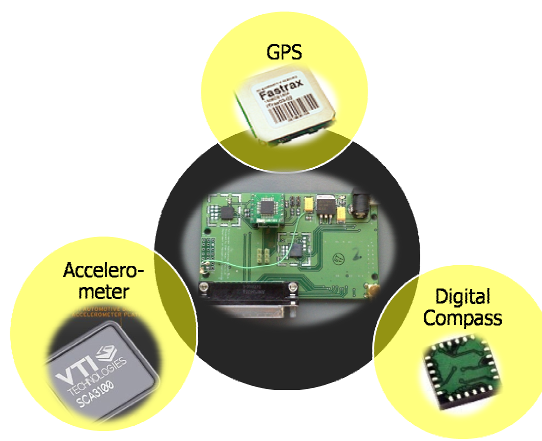

Figure 2. General picture of the MSP system.

FILTER DESCRIPTION

The recursive filtering sequence applied in the MSP implementation and the central Kalman filter fusing the different measurement sources includes prediction and update steps. A model describing the user dynamics is needed for prediction to describe the relationship between the variables over time. In addition, a statistical model for the dynamic process is necessary. The measurement update step in turn combines 'historical data' with new information. Outlier detection for different measurement sources, adaptive filter gain adjustment, and practical limits to the covariances allowed for valid outputs should be set in order for the filter to survive in various environments and to produce reliable results.

Algorithm of the Multi-Sensor Positioning Approach

The general sensor integration scheme combining the GPS output (Northing, Easting, horizontal speed, heading), sensor measurements (horizontal speed, heading), and their variance estimates is depicted in Fig. 3. We assume that the MSP device is mounted on the pedestrian in a levelled frame (on the waist as shown in Fig. 1) so that we can operate in a horizontal plane. The implementation in a horizontal plane is a temporary solution of work in progress, and future approaches of the multi-sensor platform will address the 3-dimensional pedestrian positioning problem.

The integration scheme used is a loosely coupled flexible approach which is implemented in the real time embedded processor as a serial processing implementation; a measurement type (position, speed, direction) is handled one at a time. The position, velocity, and direction domain related measurements can be processed serially to save in computational resources since certain matrix inversions are avoided, see e.g. [2].

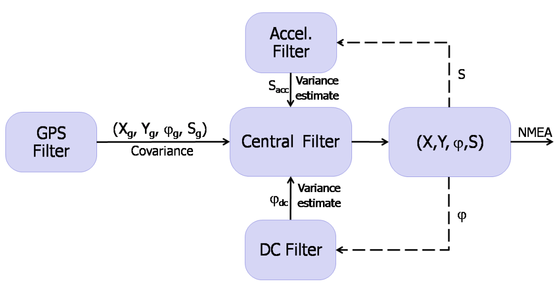

Figure 3. Integration scheme for the multi-sensor positioning approach.

A simplified representation of the central filter combining different input sources can be described with typical Kalman filter equations. The measurement model is

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k$$

where the state estimate vector is

$$\mathbf{x}_k = [X, Y, S, \varphi]^T,$$

in which X describes the North position, Y the East position, S the user horizontal velocity (speed), and φ the heading. The measurement vector is given as

$$\mathbf{z}_k = [X_g, Y_g, S_g, \varphi_g, S_{acc}, \varphi_{dc}]^T$$

where 'g' refers to GPS, 'acc' to accelerometer, and 'dc' to digital compass. The matrix $\mathbf{H}_k$ is the design matrix of the system and the vector $\mathbf{v}_k$ is the measurement error vector.

The recursive sequence applied in the implemented multi-sensor positioning approach includes prediction and update steps. The prediction step includes the typical equations of

$$\hat{\mathbf{x}}_k^- = \mathbf{\Phi}_{k-1}\mathbf{x}_{k-1}^+ \text{ and}$$

$$\mathbf{P}_k^- = \mathbf{\Phi}_{k-1}\mathbf{P}_{k-1}^+\mathbf{\Phi}_{k-1}^T + \mathbf{Q}_{k-1},$$

while the update step includes

$$\hat{\mathbf{x}}_k^+ = \hat{\mathbf{x}}_k^- + \mathbf{K}_k\left[\mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_k^-\right]$$
$$\mathbf{P}_k^+ = \mathbf{P}_k^- - \mathbf{K}_k\mathbf{H}_k\mathbf{P}_k^-$$
$$\mathbf{K}_k = \mathbf{P}_k^-\mathbf{H}_k^T\left[\mathbf{H}_k\mathbf{P}_k^-\mathbf{H}_k^T + \mathbf{R}_k\right]^{-1}$$

where the $\mathbf{\Phi}_{k-1}$ is the state transition matrix from epoch k-1 to epoch k, the $\mathbf{Q}_k$ is the covariance matrix of the system noise, $\mathbf{R}_k$ is the covariance matrix of the measurement noise, the $\mathbf{P}_k^-$ is the *a priori* covariance matrix of the predicted state $\mathbf{x}_k^-$, the $\mathbf{P}_k^+$ is the *a posteriori* covariance matrix of the updated state $\mathbf{x}_k^+$, and the $\mathbf{K}_k$ is the gain matrix.

More information on the basic loosely-coupled Kalman filtering approach applied in the described multi-sensor system can be found from, e.g. [1, 2, 3, 4].

System adaptability and robustness

The multi-sensor positioning system combines the sensor data with the navigation solution of the GPS receiver to demonstrate the ability of ubiquitous positioning and to provide a smooth pedestrian positioning trajectory. However, the sensor data or the GPS outputs are not necessarily reliable at all times. The GPS solution is subject to decreased accuracy in poor signal-conditions or is not available at all in the degraded environments of, e.g., urban canyons, indoors or tunnels. The sensors may also be disturbed by various sources, and the interference is often very complex, and difficult to recover from, especially if the error models applied fail in the local sensor filters or the sensor calibration procedures are not successful. In order to guarantee the robustness of the final solution, the system has to deal with the various situations adaptively.

In Kalman filtering, the system adaptability is obtained by adjusting dynamically the time-varying covariance matrices $\mathbf{Q}$ and $\mathbf{R}$ according to various indications. Table 1. lists the main elements used to control the covariance $\mathbf{Q}$ or $\mathbf{R}$ in this study.

Table 1. Elements analysed when adjusting filter parameters.

Indications for adapting multi-sensor system parameters
GPS geometry: number of available signals, position dilution of precision (PDOP)
Power levels of the GPS signals
Residuals of the GPS measurements
Feedback received from the local sensor filtering and information from the disturbance monitoring of each sensor
User context and the changes observed, e.g. GPS conditions, user dynamics, outdoor/indoor, etc.
Filter innovations

The innovations are the differences between the expected measurements and the actual measurements, and are denoted as

$$\mathbf{i}_k = \left[\mathbf{z_k} - \mathbf{H_k}\mathbf{x_k^-}\right]$$

The innovations vector $\mathbf{i}_k$ can be used as an efficient indicator of measurement quality and the reliability of the model being used.

The innovations are inspected for sudden "jumps" or outliers before the measurements are processed by the filter. Therefore, any outlying measurement can be de-weighted by increasing its variance in the matrix $\mathbf{R}$ or just discarded totally before it ends up decreasing the quality of the final estimate.

As to the position and speed measurements in this implementation, the following empirical quality checking is applied. If it applies for an individual measurement z that

$$\left|(\mathrm{z} - \mathrm{H}\hat{\mathrm{x}}^-)_\mathrm{k}\right| > \mathrm{A}_{\mathrm{threshold}}$$

then the variance of the measurement z is increased or it is just discarded, depending on the amount of the deviation. The threshold $\mathrm{A}_{\mathrm{threshold}}$ is relative to and chosen based on the variance of the innovation of the individual measurement z in the matrix

$$\mathbf{C_k} = \left[\mathbf{H_k}\mathbf{P_k^-}\mathbf{H_k^T} + \mathbf{R_k}\right].$$

For the heading measurement of the digital compass, the innovation is monitored over time in the current implementation by checking that if

$$\left|(\mathrm{z} - \mathrm{H}\hat{\mathrm{x}})_\mathrm{k} - (\mathrm{z} - \mathrm{H}\hat{\mathrm{x}})_{k-1}\right| > \mathrm{a}_{\mathrm{threshold}}$$

then the variance of the measurement z is increased or it is discarded altogether, depending on the amount of deviation. The threshold $\mathrm{a}_{\mathrm{threshold}}$ is chosen empirically.

Obviously, even though the measurements would be good enough, a significant error in the prediction $\mathbf{x}_k^-$ causes large innovations as the filter becomes unstable. The innovation analysis can thus be used to identify the trustworthiness of the model as well, as discussed in e.g. [2, 4, 8]), by assessing the following value

$$T_k = (\mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_k^-)^T(\mathbf{H}_k\mathbf{P}_k^-\mathbf{H}_k^T + \mathbf{R}_k)^{-1}(\mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_k^-)$$

With large values, the parameter T_k may indicate mismodeling problems. Then, the elements of the covariance matrix $\mathbf{Q}_k$ can be increased or the Kalman filter can be reset depending on the amount of deviation detected.

Currently, the adaptability and robustness checking procedures are highly empirical and base on the real data monitored on-the-fly, and more research is needed in order to further improve the procedures conducted for multi-sensor filter reliability improvement.

TEST RESULTS

Two test scenarios have been carried out. One scenario is performed in an outdoor environment in a dense forest with fairly significant foliage and signal attenuation conditions, while the other is conducted in an indoor environment of a typical office corridor of a concrete, steel and glass building. The outdoor and indoor scenarios are conducted to test the GPS/"reduced"-INS performance with respect to a standalone high-sensitivity GPS solution.

Outdoor pedestrian test in a dense forest

The outdoor pedestrian test was conducted in a dense forest path shown in Fig. 4.

Figure 4. Environment of the pedestrian outdoor test.

The GPS performance in the forest was quite good by itself already, so the improvement expectation was not significant for the multi-sensor implementation as such.

Fig. 5 presents the position result of the pedestrian forest test, and Fig. 6 presents the result of the pedestrian speed during the walk along the test route. The MSP provides a slightly smoothed walking trajectory with three of the largest error "jumps" being removed, and a more accurate speed result. Fig. 7 shows the position results also on top of a terrain map to highlight the slightly improved output of the MSP with respect to the GPS-only solution. The terrain map is used to provide a rough estimate of the true trajectory since the reference equipment failed to record the route properly in the particular test.

Due to that the GPS signal availability is quite good in the forest (though some signal attenuation is still present) the position domain result of the GPS-only solution is not that much degraded from the MSP result and they are in fact quite similar despite three outlying position solutions. The advantages of the MSP solution become more visible in a demanding signal area like indoors or during total GPS outages in e.g. tunnels. The speed result is however significantly closer to the truth with the MSP approach, as expected from the accelerometer advantages on user dynamics monitoring.

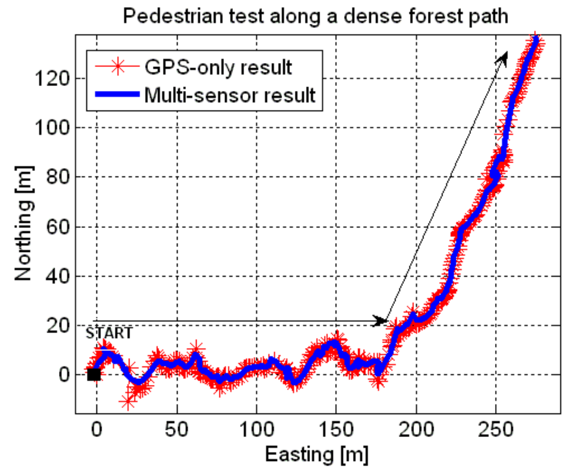

Figure 5. Position result comparison of the forest scenario.

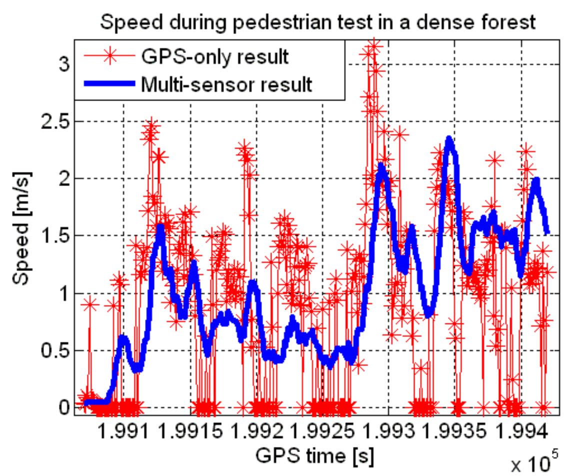

Figure 6. Speed result comparison of the forest scenario.

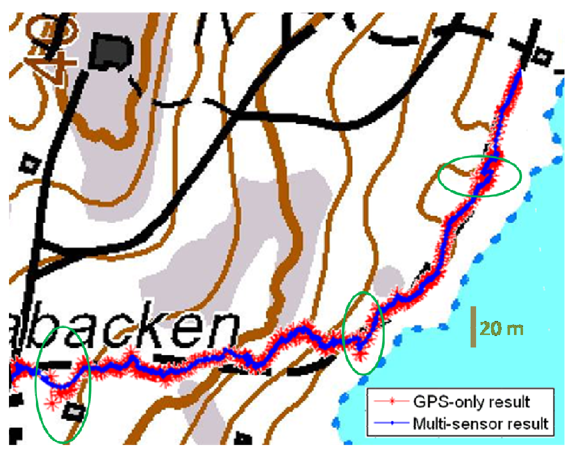

Figure 7. Forest path results presented on top of a terrain map.

Indoor pedestrian test in an office corridor

The indoor pedestrian test was conducted inside an office corridor shown in Fig. 8.

Figure 8. Environment of the pedestrian indoor test.

Fig. 9 shows the position results of the MSP and the high-sensitivity GPS-only approach in the corridor pedestrian test. The MSP provides a significantly smoother trajectory. Fig. 10 shows the same position domain outcome but on top of the building outline to point out the true trajectory more clearly, since unfortunately again the reference trajectory is lacking. Fig. 11 shows the speed result.

The high-sensitivity GPS-only solution is very noisy indoors and thus the MSP can provide a more accurate result, in all domains. The GPS used is a high-sensitivity GPS receiver, and thus the availability is high even though the signal conditions are severely degraded indoors and therefore the GPS provided accuracy is still very noisy. The advantage of the MSP processing can be seen in a smoother walking trajectory and improved speed result. The cross-track accuracy is much improved with the multi-sensor approach, as can be seen from Figures 9 and 10, though it is still not optimal and further work is needed to improve the result with additional sensors and technologies.

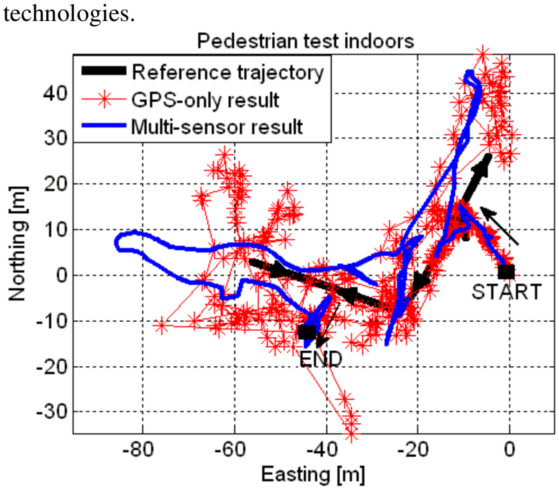

Figure 9. Position result comparison of the indoor scenario.

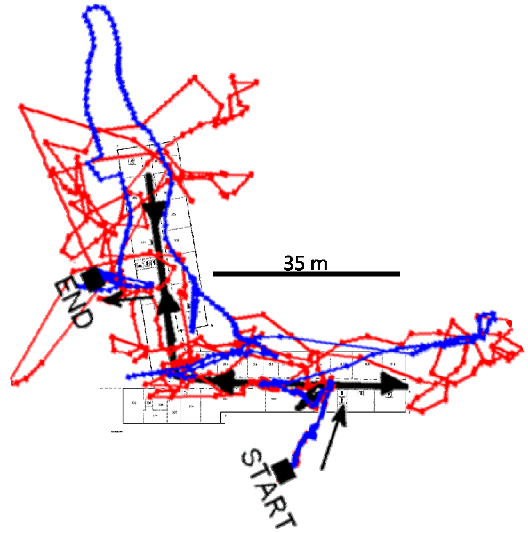

Figure 10. Indoor pedestrian result presented on top of the reference building.

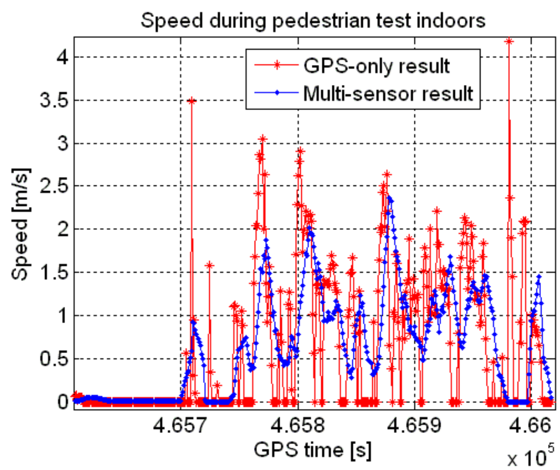

Figure 11. Speed result comparison of the indoor scenario.

CONCLUSIONS

This paper presents a simple multi-sensor GPS/reduced-self-contained sensor approach for pedestrian positioning: combining a GPS receiver, a digital compass and a 3-axis accelerometer. The multi-sensor positioning system is dedicated to personal navigation in a GNSS degraded environment, e.g. an urban canyon, a forest, or indoors. The Kalman filter is used to fuse the multi-sensor data. As GPS and self-contained sensors both may be interfered and have degraded performance, the filter system must have the adaptability and robustness to deal with possible contaminated measurements.

This paper also presents test results of two typical pedestrian scenarios: a dense forest and an indoor corridor. The multi-sensor positioning system performs well on both scenarios. In the forest testing, the multi-sensor positioning system works slightly better than standalone GPS, although the high sensitivity GPS receiver has high availability and good performance also by itself. In the indoor testing, the advantages of the multi-sensor positioning system are more evident as the MSP solution is more accurate in position and velocity domains and closer to the true corridor trajectory than the GPS-only solution.

The presented multi-sensor platform is still work-in-progress, and future steps to improve its performance include adding more sensors to the platform (a barometer, gyros) as well as utilizing multi-network approaches, e.g. making use of wireless LAN (WLAN) or Bluetooth fingerprinting as a source for indoor position.

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