

An Intelligent Multi-sensor System for Pedestrian Navigation

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Abstract. In the research project “Pedestrian Navigation Systems in Combined Indoor/Outdoor Environments” (NAVIO) we are working on the development of modern intelligent systems and services for pedestrian navigation and guidance. In the project modern and advanced intelligent mobile multi-sensor systems should be employed for 3-D position determination of a user. Due to the fact that satellite positioning with GNSS (Galileo, GPS, etc.) does not work under any environmental condition (e.g. in urban “canyons” with no satellite visibility and indoor) a combination and integration with other sensors (e.g. dead reckoning sensors, inertial navigation systems (INS), indoor location techniques, cellular phone positioning, etc.) is essential. In our approach a loose coupling of the employed sensors should be achieved and it is proposed to develop a multi-sensor fusion model which makes use of knowledge-based systems. As far as we can see now knowledge-based systems can be especially useful. Thereby the decision which sensors should be used to obtain an optimal estimate of the current user’s position and the weightings of the observations shall be based on knowledge-based systems. The new algorithm would be of great benefit for the integration of different sensors as the performance of the service would be significantly improved. In this paper the basic principle of the new approach will be described. To test and to demonstrate our approach and results, the project takes a use case scenario into account, i.e., the guidance of visitors to departments of the Vienna University of Technology from nearby public transport stops. The results of first field tests could confirm that such a service can achieve a high level of performance for the guidance of a pedestrian in an urban area and mixed indoor and outdoor environments. Standard deviations in the range of few meters can be achieved for 3-D positioning in urban areas although obstructions cause frequent loss of lock for satellite positioning. Thereby GPS outages of up to 150 m can be bridged using dead reckoning observations with the required positioning accuracy. For indoor areas satellite positioning can be replaced by indoor positioning systems (e.g. WiFi, UWB). Due to the development of advanced sensors it can be expected that such multi-

sensor solutions will be deployed in pedestrians navigation services. We believe that these services will play an important role in the field of location-based services in the near future as a rapid development has already started which is driven by their possible applications.

Keywords. Pedestrian Navigation, Integrated Positioning, Multi-Sensor Fusion, Kalman Filter, Knowledge-Based Systems.

1 Introduction

In the research project NAVIO (Pedestrian Navigation Systems in Combined Indoor/Outdoor Environments) we are working on the development of modern intelligent navigation systems and services for pedestrian navigation and guidance. Thereby the research work is performed in three different work packages, i.e., the first on “Integrated positioning”, the second on “Pedestrian route modeling” and the third on “Multimedia route communication”. To test and to demonstrate our approach and results, the project takes a use case scenario into account, i.e., the guidance of visitors to departments of the Vienna University of Technology (Gartner et al., 2004).

In this paper we will concentrate on the research work and findings in the first work package. Challenging tasks that are dealt with here are:

- the capability to track the movements of a pedestrian in real-time using different suitable location sensors and to obtain an optimal estimate of the current user’s position,
- the possibility to locate the user in 3 dimensions with high precision (that includes to be able to determine the correct floor of a user in a multi-storey building), and

- the capability to achieve a seamless transition for continuous positioning determination between indoor and outdoor areas.

Thereby a navigation support must be able to provide location, orientation and movement of the user as well as related geographic information matching well with the real world situation experienced by pedestrians. Usable location sensors have been classified and the most suitable ones for guidance and navigation services were selected. For pedestrian navigation systems suitable location technologies include GPS/GNSS and indoor location techniques, cellular phone positioning, dead reckoning sensors (e.g. magnetic compass, gyros and accelerometers) for measurement of heading and traveled distance as well as barometric pressure sensors for altitude determination (Retscher, 2004).

Our proposal and a part of our future research work is focused on the development of modern and advanced intelligent mobile multi-sensor systems that can be employed for any personal navigation application especially in the field of location-based services. Due to the fact that satellite positioning with GNSS (Galileo, GPS, etc.) does not work under any environmental condition (e.g. in urban ‘canyons’ with no satellite visibility and indoor) a combination and integration with other sensors (e.g. dead reckoning sensors, inertial navigation systems (INS), cellular phone positioning, etc.) is essential. In our approach a loose coupling of the employed sensors in the sense of a hybrid multi-sensor system should be achieved. Therefore it is proposed to develop a multi-sensor fusion model which makes use of knowledge-based systems. As far as we can see now knowledge-based systems can be especially useful. Thereby the decision which sensors should be used to obtain an optimal estimate of the current user’s position and the weightings of the observations shall be based on knowledge-based systems. The new algorithm would be of great benefit for the integration of different sensors as the performance of the service would be significantly improved. The main development will be focused on the deduction of a multi-sensor fusion model based on knowledge-based systems. In this paper the basic principle of the new approach will be described.

As a practical example, the guidance of a visitor of the Vienna University of Technology from public transport stops to our department is investigated in the NAVIO project. First test results of the dead reckoning sensors will be presented in the paper.

2 Concept of an Intelligent Multi-Sensor Fusion Model

The integration of different sensors and location methods shall be based on an intelligent multi-sensor fusion model

in the project NAVIO. Thereby the current position of a user is estimated using a Kalman filter approach which makes use of knowledge-based systems. Figure 1 shows a process flow of the intelligent multi-sensor fusion model. Firstly the observations of each sensor and location technique of the multi-sensor system are analyzed in a knowledge-based preprocessing filter. In this step the plausibility of the observations is tested as well as gross errors and outliers are detected and eliminated. The analyzed and corrected observations are then used in the following central Kalman filter for the optimal estimation of the current user’s position and its velocity and direction of movement. In this processing step all suitable sensor observations as identified before are employed and the stochastic filter model is adapted using the knowledge of the preprocessing step. For example, the weightings of the GPS observations can be reduced in the case if the current GPS positioning accuracy is low due to a high GDOP value (i.e., bad satellite-receiver geometry). Then the optimal estimate of the user’s position should be more based on the observations of other sensors (e.g. dead reckoning observations).

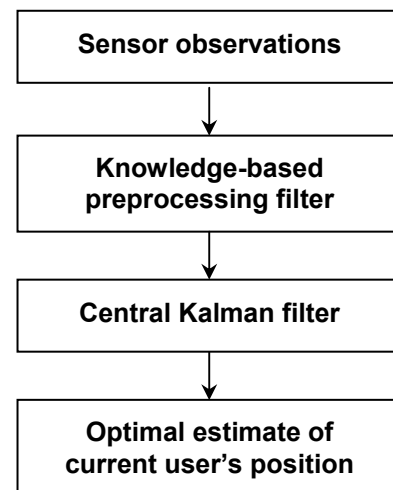


Fig. 1 Process flow of the intelligent multi-sensor fusion model (after Retscher, 2005)

In the following the principle of the knowledge-based preprocessing filter will be discussed in more detail.

3 Principle of Knowledge-Based Systems

To provide an automated preprocessing of the sensor observations, a knowledge-based approach has been chosen. In the following, the basics underlying knowledge-based systems are briefly described.

Programs which emulate human expertise in well defined problem domains are called knowledge-based systems (see e.g. Stefik, 1998) and they are the results of research in the area of artificial intelligence. Their main

advantages in comparison with conventional programming languages (such as Delphi, Fortran and C++) are (see Reiterer et al., 2003):

- the knowledge about the problem domain is separated from general problem-solving knowledge which makes it easier for the knowledge engineer to manipulate this knowledge;
- experts knowledge that exists very often in form of rules can be captured in this form without converting into forests of data definitions and procedures.

Thereby the knowledge-based system consists of the following major components: a knowledge base, an inference engine, an user interface, a knowledge acquisition tool and an explanation tool (Stefik, 1998). Various schemes for knowledge representation can be employed, e.g. rules, frames, semantic nets and others. Each has its peculiar strengths and weaknesses. The structure of a rule-based approach is very similar to the way how people solve problems. Thereby human experts find it convenient to express their knowledge in form of rules (i.e., situation – action pairs). Furthermore rules are a way to represent knowledge without complex programming constructs (Reiterer et al., 2003).

For the implementation of a knowledge-based system in practice different approaches can be selected, e.g. procedural methods, object oriented methods, logical based methods, etc. In practice also combinations of the different methods are employed. For the implementation of the knowledge-based preprocessing filter a rule-based object oriented approach was selected (Retscher, 2005).

The rule-based system consists of two components, i.e., a working memory (WM) and a set of rules or the so-called rule memory (Brownston et al., 1985). The WM is a collection of working memory elements which itself are instantiations of a working memory type (WMT). WMT's can be considered as record declarations in PASCAL or struct declarations in C. The second component of a rule-based system are the rules. The rule base is divided into three groups of rules, i.e.,

- rules for the choice of suitable algorithms,
- rules for the predefinition of necessary parameters, and
- rules to define the order of the algorithms.

A rule is divided into two parts, namely the lefthand side (LHS) and the righthand side (RHS). In the LHS the preconditions of the rule are formulated, whereas in the RHS the actions are formulated. A rule can be applied (or 'fired') if all its preconditions on the LHS are satisfied. Then the actions specified in the RHS are executed. Rules can be seen as so-called IF-THEN statements, e.g.

IF (condition 1 AND condition 2) THEN (action). (1)

There are algorithms for the so-called matching phase, i.e., the phase where all rules are checked against all working memory elements which are efficient in practice. The result of the matching phase is the 'conflict set' which includes all rule instances 'ready to be fired'. A conflict resolution strategy selects one rule instance which is actually fired (Reiterer et al., 2003).

The coding of the rule is performed in the chosen programming language. For the knowledge-based preprocessing filter an implementation based on CLIPS (2005) or wxCLIPS (2005) will be performed.

The processing of the rules is performed as described above. In the case under consideration this process is performed in a forward-reasoning following the recognize-act-cycle. In forward-reasoning a specific rule is selected from an existing database which fulfills the preconditions of the database and then its action part is applied (or fired) where the action changes the existing database. This process is repeated as long as no rule can be applied anymore (Puppe, 1991). The recognize-act-cycle consists of the following three steps, i.e.,

- the examination as a first step where all rules are tested about their feasibility,
- the selection of the rule as a second step where a specific rule from the preselection is selected, and
- the action as a last step where the selected rule or its action part is applied.

This cycle is run as long as no rule can be executed anymore or if a stop signal is given.

4 Central Kalman Filter

After the preprocessing filter, an optimal estimation of the current user's position and its velocity and direction of movement is performed in a central Kalman filter using all suitable observations from the sensors and location techniques. Using this recursive approach the state of the movement of the pedestrian can be estimated based on the use of theoretical assumptions about the user's movement behavior and current observations. Thereby the user's movement behavior is formulated in the system equations and the observations are introduced in the measurement equation of the filter. The Kalman filter provides then an exact solution to the linear Gaussian filtering problem and the problem is characterized completely by its state vector and covariance matrix. The filtering process is reduced to the prediction and updating of these two statistical parameters (see e.g. in Gelb, 1986; Schrick, 1997).

For the system equations of the filter a 3-D kinematic motion model is employed which enables the prediction of the state of the movement of the pedestrian (e.g. the

current position, velocity and heading) from one epoch to the next. Depending on the type of the model different parameters can be included in the state vector $\bar{x}(k)$. The following parameters can be used to describe the state of the system (see Retscher and Mok, 2004; Retscher, 2004):

- 3-D coordinates of the current position y, x, z of the user,
- 3-D velocities v_y, v_x, v_z ,
- 3-D accelerations a_y, a_x, a_z ,
- direction of motion (heading) φ in the ground plane xy ,
- velocity v in the ground plane xy ,
- radial acceleration a_{rad} in the ground plane xy .

If the state vector $\bar{x}(k)$ includes only 6 parameters, i.e., the 3-D coordinates of the current position y, x, z and the

velocities v_y, v_x, v_z , the kinematic model describes a constant linear movement. A constant accelerated movement is described with 9 parameters in the state vector where in addition to the previous model also the 3-D accelerations a_y, a_x, a_z are included in the kinematic model. A constant radial movement can be described by different parameters in the state vector, i.e., the 3-D coordinates of the current position y, x, z , the heading φ , the velocity v and the radial acceleration a_{rad} in the ground plane xy and the velocity v_z in z -direction. Using these models the filter predicts slightly different the movement of the user where in the first model compared to the second no accelerations are used and in the third model a radial movement without tangential accelerations a_{tan} is employed. Simulations have shown that the third model gives a good approximation to describe the movement behavior of a pedestrian (Retscher and Mok, 2004).

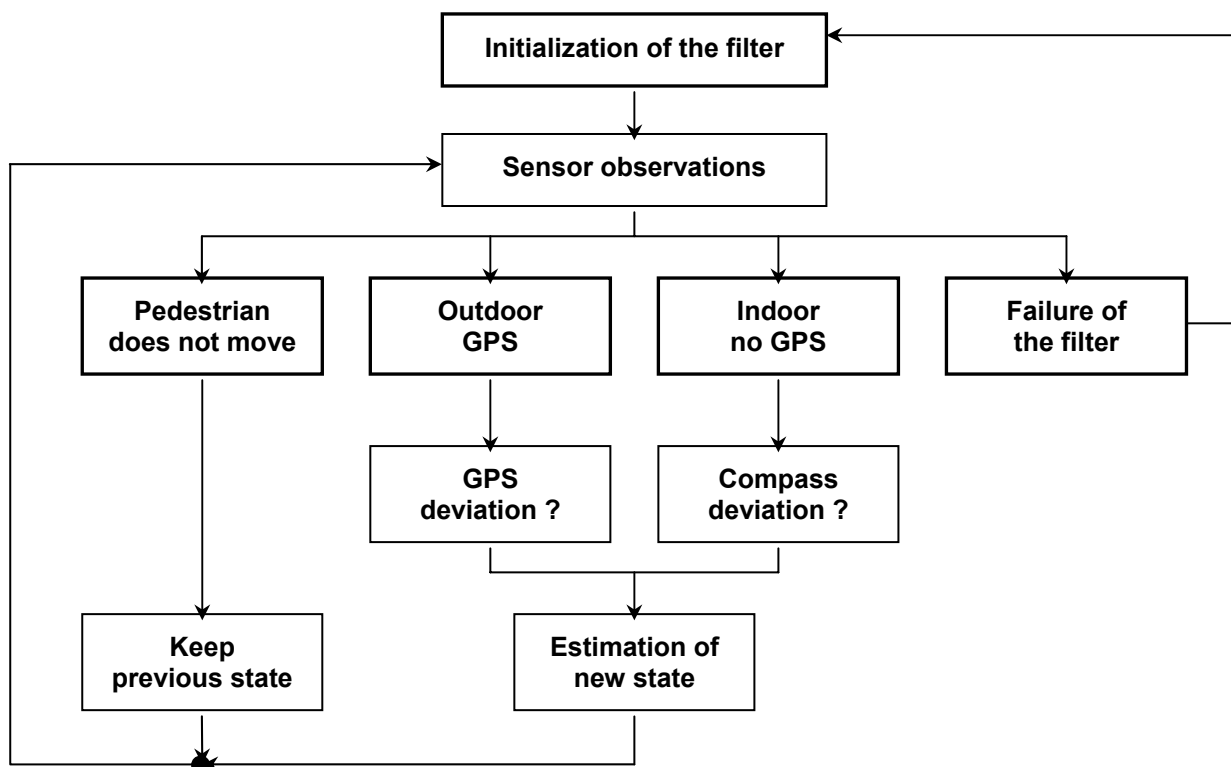


Fig. 2 Architecture of the central Kalman filter (after Retscher, 2005)

Figure 2 shows the architecture of the central Kalman filter. It consists of four different modules which describe either the current environment of the pedestrian (outdoor or indoor area) or the movement of the pedestrian (pedestrian moves or does not move) or takes into account a possible failure of the filter. Thereby of great importance is the detection of bad GPS quality in outdoor

environments due to e.g. bad satellite-receiver geometry (high GDOP value) or multipath. From the results of the knowledge-based preprocessing filter an additional statistical evaluation of the deviations between the kinematic motion model and the GPS observations (e.g. using tests of the innovation, i.e., the difference between the real observations and the predicted measurements, in

the Kalman filter) and an adequate weighting of the GPS observations in the stochastic filter model is performed. In the indoor environment the filter estimate is mainly based on the observations of the dead reckoning sensors. This is the case if no other indoor location system is employed that provides absolute coordinates of the user (e.g. WiFi fingerprinting; see Retscher, 2004). The dead reckoning observations depend thereby mainly on the output of the heading sensor (i.e., digital compass). Similar to the analysis of the GPS observations in the outdoor environment, the observations of the digital compass are analyzed for gross errors or outliers and their weight for the Kalman filter is derived. In the case if the pedestrian does not move the observations are not used to determine a new position estimate but the previous determined state is kept. If a failure of the filter occurs a reinitialization is required (Retscher, 2005).

5 Sensors for Pedestrian Navigation

The integration of different location technologies and sensors is essential for the performance of modern advanced navigation systems. Thereby common navigation systems rely mainly on satellite positioning (GNSS) for absolute position determination. Losses of lock of satellite signals are usually bridged using dead reckoning (DR) observations. Due to the main limitations of the sensors (i.e., satellite availability in the case of GNSS and large drift rates in the case of DR) other positioning technologies should be integrated into the system design of a personal navigation system to augment GNSS and DR positioning.

Other radio positioning systems and wireless geolocation technologies have been developed and can be employed in personal navigation systems. Following Pahlavan et al. (2002) two basic approaches can be distinguished in the development of wireless geolocation techniques, i.e., one approach where the system is solely designed for positioning using certain radio signals and the second where already established wireless infrastructure (e.g. WiFi or UWB) is employed for location determination. Thereby the second approach has the advantage that usually no additional and costly hardware installations are required. Some of these systems have been especially developed for indoor applications, but they can also be employed in indoor-to-outdoor and urban environments (Retscher and Kealy, 2005). One approach is the use of WiFi signals for position determination. The basic principle of this approach has been analyzed and can be found in Retscher (2004). In a study the performance of a WiFi fingerprint method has been recently tested and it can be summarized that positioning accuracies in the range of 1 to 3 m can be achieved.

In addition, for the pedestrian navigation service in our research project NAVIO the following dead reckoning (DR) sensors are employed:

- dead reckoning module DRM III from PointResearch,
- Honeywell digital compass module HMR 3000,
- Crossbow accelerometer CXTD02, and
- Vaisala pressure sensor PTB220A.

The dead reckoning module DRM III from PointResearch (2005) is a self contained navigation unit where GPS is not required for operation. It provides independent position information based on the user's stride and pace count, magnetic north and barometric altitude. The module is designed to self-calibrate when used in conjunction with an appropriate GPS receiver, and can produce reliable position data during GPS outages. The system consists of an integrated 12 channel GPS receiver, antenna, digital compass, pedometer and altimeter. The module is clipped onto the user's belt in the middle of the back and the GPS antenna may be attached to a hat. Firmware converts the sensor signals to appropriate discrete parameters, calculates compass azimuth, detects footsteps, calculates altitude and performs dead reckoning position calculation. An internal Kalman filter algorithm is used to combine dead reckoning position with GPS position to obtain an optimum estimate for the current user's position and track. With the dead reckoning module and GPS integrated together, a clear view of the sky is only required for obtaining the initial position fix. The fix must produce an estimated position error of 100 m or less to begin initialization. Subsequent fixes use both dead reckoning and GPS data, so obstructed satellites are not as critical as in a GPS only configuration. The Kalman filter continuously updates calibration factors for stride length and compass mounting offset. The GPS position error must be less than 30 m before GPS data will be used by the Kalman filter, and the first such fix will also initialize the module's latitude and longitude. Subsequently, the filter will use any GPS position fix with an estimated position error of 100 m or less, adjusting stride, body offset, northing, easting, latitude and longitude continually.

The Honeywell digital compass module HMR 3000 is employed in the project NAVIO for precise heading determination of the pedestrian. The HMR 3000 consists of a magnetic sensor and a two-axis tilt sensor (Honeywell, 2005). The low power, small device is housed in a non-magnetic metallic enclosure that can be easily installed on any platform. A sophisticated auto compass calibration routine will correct for the magnetic effects of the platform. Wide dynamic range of the magnetometer allows the HMR 3000 to be useful in applications with large local magnetic fields. The influence of magnetic disturbances on the sensor has been

tested and is presented in Retscher and Thienelt (2005). It could be seen that deviations of only 2 to 3 degrees occurred if the source of disturbance (e.g. a notebook computer or a metallic lighter) is put in a distance of about 30 cm from the sensor. Higher deviations occur, however, at shorter distances to the sensor. As a consequence the sensor should be kept away from mobile phones, coins, metallic lighters and keys.

For measurement of the accelerations of the pedestrian the Crossbow accelerometer CXTD02 should be employed. The CXTD02 is a tilt and acceleration sensor and measures tilt and acceleration using a triaxial MEMS accelerometer (Crossbow, 2005). It provides high performance in more demanding measurement applications where high accuracy must be maintained over a wide temperature range. The low noise floor and true DC response guarantees a long-term stability. It should be analyzed in detail how the sensor can be employed for the determination of the traveled distance, pitch and roll of the sensor platform.

In addition, the Vaisala pressure sensor PTB220A is employed in the project for determination of height differences from changes of the air pressure. The PTB220A is designed for measurements in a wide environmental pressure and temperature range with an extremely high accuracy (Vaisala, 2005). Starting from a given height the pressure changes can be converted in changes in height using the following equation:

$$\begin{aligned} \Delta H &= H_2 - H_1 = \\ &= 18464 \cdot (1 + 0,0037 \cdot t_m) \cdot (\lg B_1 - \lg B_2) \end{aligned} \quad (2)$$

where ΔH is the height difference between two stations 1 and 2, B_1 and B_2 are the pressure observations at station 1 and 2 and t_m is the mean value of the temperature of both stations.

It must be noted that this equation is an approximation formula that is valid for central Europe only (Kahmen, 1997).

Recently performed tests have shown that we are able to determine the correct floor of a user in a multi-storey building using this sensor (see also Figure 5).

6 Sensor Tests

Practical tests in the NAVIO project are carried out for the guidance of visitors of the Vienna University of Technology to certain offices in different buildings or to certain persons. Thereby we assume that the visitor employs a pedestrian navigation system using different sensors that perform an integrated positioning. Start points are nearby public transport stops, e.g. underground station Karlsplatz in the center of Vienna. Tests with two

different GPS receivers have been carried out in this area and are presented in Retscher and Thienelt (2004). Because of obstructions caused by the surrounding four to five storey buildings it frequently happens that GPS signals are lost so that large parts of the route of the pedestrian must be bridged by dead reckoning. Only in a park at the exit of the underground station and on isolated road crossings it is possible to receive GPS signals with sufficient quality. This area is therefore suitable for testing the combination of absolute and relative DR location sensors. Further sensor tests are scheduled to be performed in the next months in this area.

First test measurements with the dead reckoning module DRM III from PointResearch (2005) have been carried out in another test area in the park of Schönbrunn Palace in Vienna shown in Figure 3. This test site has been chosen as it provides free satellite visibility. Figure 4 shows the dead reckoning observations as well as the GPS measurements along a 475 m long track in the park of Schönbrunn Palace. In the dead reckoning module, measurements of accelerometers are employed to count the steps of the walking pedestrian and the traveled distance is obtained using a predefined value for the stride length. Using GPS observations the stride length can be calibrated. Furthermore a compass and a gyro are employed for measurement of the heading or direction of motion. The dead reckoning observations shown in Figure 4 have been obtained without using the GPS calibration. They reach deviations in the range of 7 m over a distance of 150 m and 20 m over 200 m from the given track. The GPS measurements have a maximum deviation of 7 m. Figure 4 shows also the resulting trajectory from the internal Kalman filter of the DRM III module calculated from a combination of GPS and DR observations. It can be seen that the large drift rate of the DR observations can be reduced. Using the DR observations, GPS outages (i.e., when GPS is unavailable) of up to 150 to 200 m can be bridged with a reasonable positioning accuracy. For longer GPS outages, however, other location technologies have to be employed providing an absolute position estimate to correct for the DR drift.

Figure 5 shows test observations with the Vaisala pressure sensor PTB220A in our office building of the Vienna University of Technology. This building has 5 storeys and our department is located on the 3rd floor. It can be clearly seen in Figure 5 that the sensor is able to determine the correct floor of the user with a high precision. The standard deviation of the pressure observation is in the range of ± 0.2 hPa and the maximum deviation of the determined height is less than ± 1 m for 90 % of the observations.

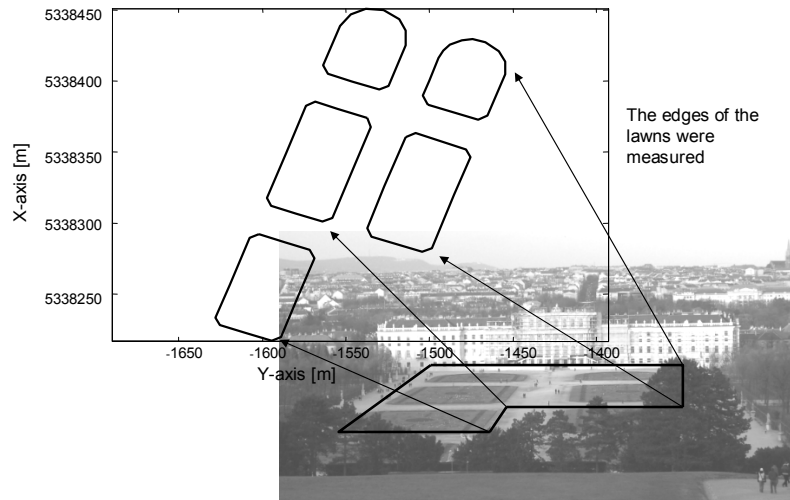


Fig. 3 Field test site in the park of Schönbrunn Palace in the city of Vienna

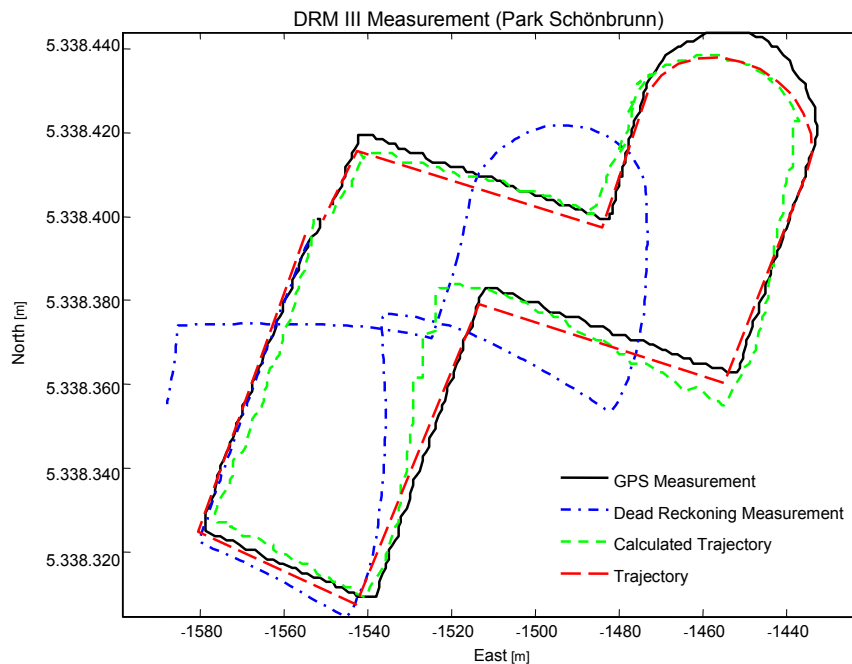


Fig. 4 Test measurements with the dead reckoning module DRM III in the park of Schönbrunn Palace in Vienna

The results of the different tests could confirm that a pedestrian navigation service can achieve a high level of performance for the guidance of a user in an urban area and mixed indoor and outdoor environments. Standard deviations in the range of few meters can be achieved for 3-D positioning in urban areas although obstructions cause frequent loss of lock for satellite positioning. Thereby GPS outages of up to 150 m can be bridged using dead reckoning observations in combination with cellular positioning with the required positioning accuracy. For indoor areas satellite positioning can be replaced by indoor positioning systems (e.g. WiFi

fingerprinting; see Retscher, 2004) and the altitude of the user can be observed using a barometric pressure sensor.

7 Conclusions

From the presented sensor tests can be seen that a high precision and reliability for the position determination of a pedestrian can be achieved if different location techniques and dead reckoning sensors are employed and combined. For the integration of all observations a new multi-sensor fusion model based on an extended Kalman filter which makes use of a knowledge-based

preprocessing of the sensor observations can be applied. The principle of this new approach is presented in the paper. The knowledge-based preprocessing filter represents an extension of common multi-sensor fusion models in a way that the data based system analysis and modeling is supplemented by a knowledge-based component and therefore not directly quantifiable information is implemented through formulation and application of rules. This rules are tested in the preprocessing step and if they are fulfilled certain actions are executed. Due to the knowledge-based analysis of the sensor observations gross errors and outliers can be detected and eliminated. In addition, the preprocessing filter supplies input values for the stochastic model of the central Kalman filter. Therefore the weightings of the sensor observations can be adjusted in the Kalman filter depending on the availability and quality of the current observations. This approach will be implemented and further sensor tests will be carried out. Due to the development of advanced sensors it can be expected that such multi-sensor solutions will be deployed in pedestrians navigation services in the near future. We believe that these services will play an important role in the field of location-based services.

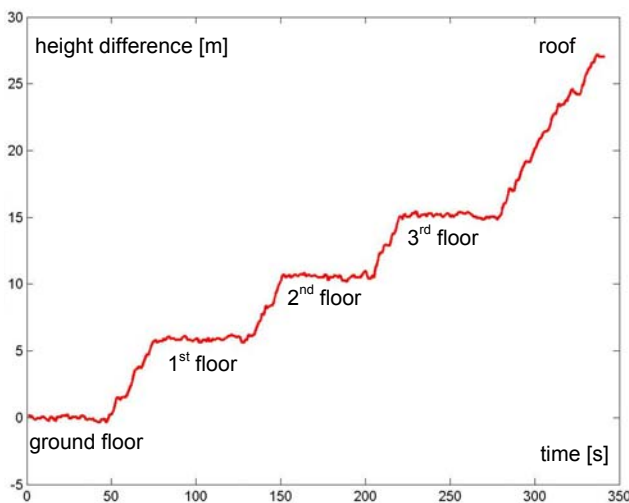


Fig. 5 Test measurements with the Vaisala pressure sensor PTB220A in our office building of the Vienna University of Technology

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