UKF Sensor Data Fusion for Localisation of a Mobile Robot

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Abstract

The localisation of outdoor mobile robots is one of the most important challenges for implementing applications such as search and rescue, reconnaissance, surveillance and monitoring. The Global Positioning System (GPS) is a common used sensor system for localisation but the drawbacks of its limited accuracy are well known. These effects can cause mission failure especially for small sized mobile robots. To compensate these drawbacks, a sensor data fusion is introduced based on an Unscented Kalman Filter (UKF) that fuses GPS, inertial and incremental sensor data in an adaptive way. In case of GPS outages the typical INS drift can be avoided by a new alternative position update, which is calculated based on the last pose and the kinematic model that uses incremental encoder and yaw rate sensor data. The whole system is implemented on a low power micro controller.

1 Introduction

Since the 1990s small outdoor rovers were developed for different applications such as search and rescue, surveillance, monitoring, emergency and security. In all these applications one essential task is self-localization that enables the navigation of the robot. Without any positioning system autonomous as well as tele-operated applications cannot be performed successfully.

Frequently used approaches to localizing the robot are based on previous knowledge of the area. Either they perceive the environment and try to match the sensor data to a known map or the robot searches for known landmarks and tries to match these to a known map. Nevertheless, both approaches can only be used in predefined areas with existing maps. *Simultaneous localization and mapping* (SLAM) resolves the pre-knowledge of the maps. This approach builds a map of the environment online and therefore a robot can be navigated in the unknown area. But the construction of the maps needs a lot of processing power and sensors for environment perception. However none of these approaches is able to determine the global position of the robot.

Since the *global positioning system* (GPS) has been available, there exists the ability to determine the global position of robots without any pre-knowledge. Using GPS robots can be navigated all over the world. Due to the inaccuracy of GPS [1] small robots cannot be navigated in narrow passages successfully [2]. Hence the fusion of GPS with an *inertial navigation system* (INS) is able to overcome the short-therm inaccuracy of GPS. Furthermore the long-term accuracy of GPS compensates the accumulated errors of INS systems. Modern miniaturization techniques in electronics enable the usage of small sensors, the so-called *micro-electro-mechanical systems* (MEMS), without the reduction of accuracy. Different fusion approaches have already been published, which are based on Kalman filter, extended Kalman filter, fuzzy controller and so on. In this paper a new approach using an *unscented Kalman filter* (UKF) [3] will be introduced. This UKF fuses the sensor data of a GPS receiver, one gyroscope, one incremental sensor and three accelerometers. A loosely coupled approach was used to fuse the data. The filter was implemented on the Outdoor MERLIN mobile robot that was developed at the University of Würzburg.

An overview of the state of the art and the related works is summarized in the next section. Section 3 will introduce the mobile robot Outdoor MERLIN, which was used as test platform. A detailed explanation of the UKF and the sensor fusion will follow. Experiments and the results are outlined in Section 5. Finally, the last section will summarize the paper and point out the results and future work.

2 State of the Art

Localization is a huge research field where lot of studies and experiments are performed to achieve maximum accuracy in the determination and tracking of the pose of a mobile object like a mobile robot. The most likely pose of a robot is the result of the fusion of different types of sensor data. When these sensors are attached to a mobile robot then the whole system is called a *strapdown system*. Complimentary sensor types like an *inertial navigation system* (INS) and the *Global Positioning System* (GPS) are fused to yield a system which combines the positive characteristics of the complimentary sensors. The positive effects of this combination is well known and documented [1, 4, 2, 5]. The basic GPS/INS navigation system can be divided into three integration types where the most common one is known as a *loosely coupled approach*. In this approach both navigation systems, GPS and INS, reside

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independently next to each other and the results of both systems are fused by a filter to yield a better pose solution. Besides this basic system newer approaches like the *tightly coupled approach* and the *deep integration* are topics of more recent studies, in which both navigation systems are fused together to one working unit. In general this improves the accuracy and the reliability of the GPS/INS integration [6, 2]. To improve the accuracy of the position estimate of the basic GPS/INS integration, the system is often extended by additional sensors like odometry, incremental, ultra sonic and visual sensors [7]. Odometry and incremental sensors can in general help to improve the pose solution whereas ultra sonic and visual sensor assistance is only feasible in a known environment with an underlying map to perform map matching.

Besides the different GPS/INS integration types and sensor combinations, the fusing filters are another wide research field. If the characteristics of the used sensors are well known then Bayes filters especially the Kalman filter family is mostly the first choice. The Kalman filters are mathematically easy to address and have a minor computational complexity in contrast to other filters [8, 9]. In navigation applications the most common used Kalman filters are the linear *Kalman filter* (KF) and the *extended Kalman filter* (EKF). The KF and the EKF are studied in lot of variations and are well documented [8, 10, 11, 12]. A more recent research topic of the Kalman filter is the class of the *sigma point Kalman filters* (SPKF) [13, 14, 15]. This filter class uses the unscented transformation and describes the probability distributions with the so-called sigma points. Studies show that SPKF delivers better results in the pose estimation compared to KF or EKF solutions [16]. The Kalman filter approach can be extended by an artificial intelligence filter in terms of neural networks to improve the performance during GPS outages [17]. During GPS outages no update of the position estimate can be performed which in turn can lead to a poor performance of the localization system. This extension can attenuate position errors significantly during outages up to a minute [17]. On the other hand, neural networks are in general computationally expensive and not feasible for low power and low cost systems [17].

Another popular filter type is the particle filter [18, 19]. A particle filter enables to gain an exact estimation of the probability density, which does not need to be unimodal in contrast to Kalman filters. The performance and the computational complexity of this filter type is directly dependent on the number of particles. Experiments have shown that particle filters can provide more accurate position estimates than Kalman filters but with a higher computational effort [20]. Of course even other algorithms like fuzzy systems or wavelet filters can also be used but these techniques are mainly used as extensions or for error compensation prior the sensor data fusion [21, 22, 23].

3 Outdoor MERLIN Mobile Robot

This section introduces the *Outdoor MERLIN* mobile robot. The robot was used as test platform for the implementation of the sensor fusion and the localization was especially adapted to this robot.
The Outdoor MERLIN belongs to the *MERLIN* (Mobile Experimental Robots for Locomotion and Intelligent Navigation) family [24] that includes the Outdoor MERLIN, the Indoor MERLIN and the Tracked MERLIN. These robots are built of the same electronic devices and sensors but they have different propulsion systems (wheeled and tracked). One advantage of the MERLIN family is the modular system design concept as well as the flexible and adaptable control software. Every rover in the MERLIN family offers the same payload and sensor interface (CAN-Bus) to guarantee a high degree of flexibility. This allows a simple change of sensors and algorithms between the rovers for different application.
The dimensions of the Outdoor MERLIN are 50 cm $\times$ 40 cm $\times$ 40 cm (length $\times$ width $\times$ high). Its weight is below 20 kg, including a payload of 5 kg. The four wheel drive robot can reach velocities up to 40 km/h. The Outdoor MERLIN is a car-like mobile robot with a front wheel steering (see Fig. 1).
A battery provides 21.6 volt for all systems on the rover. DC/DC converters offers stabilized 5 V and 12 V for the electronics. For the onboard data handling the microcontroller C167 is used. A special PCB offers an easy to use interface to a huge amount of available microcontroller interfaces, e.g. six UARTs, 4 PWM outputs, I^2C, CAN, GPIO and 16 ADC. The rover is equipped with different sensors: gyroscope, incremental sensor, inclinometer for roll and pitch, infrared sensors, 10 ultrasound sensors, GPS receiver and accelerometers [25, 26]. The incremental sensor is connected to the actuator, thus only the motor revolutions can be measured. The gyroscope is integrated on the steering axle and the accelerometers are mounted in the geometric center of the robot. A front and a rear camera are integrated on the robot for tele-operation.

Figure 1: The modular rover Outdoor MERLIN for harsh environments

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The communication link to the control station is realized with a standard WLAN connection.
A modular operating system is running on the C167, the so called MERLIN Operating System (MOS). All sensor interfaces and functions are encapsulated in modules. Hence the MOS provides a robust and reliable module management. The modules are ordered in different layers, according to their application. Basic functions, like steering or acceleration are low level modules. Modules with more sophisticated capabilities are in higher levels and can combine low level functionalities into their application [27].
The implementation of the introduced localization algorithm is encapsulated in a module inside the MOS. It include some low level modules as interface to the sensors. Hence, in future the localization can be used by a path planning and a path following module to control the Outdoor MERLIN more accurate.

4 Sensor Data Fusion

The sensor data fusion is achieved with the use of an unscented Kalman Filter. The first subsection presents the concept behind the unscented Kalman filter and afterwards the sensor fusion mechanism will be described.

4.1 Unscented Kalman Filter

Information about the state of dynamical processes is usually delivered through noisy measurements where the noise can be modeled with random variables of normal distribution. The state of such processes is commonly estimated with the use of recursive state estimators. An important family of recursive state estimators is given by the so-called Gaussian filters where all believes are represented with random variables of normal distribution.
The *Kalman filter* algorithm [28, 29] is a well-known technique for the optimal (minimum variance) estimation of the states of linear Gaussian processes. It consists of a prediction and an update phase. During the prediction, the system model is used to predict the values of the measured variables and in the update step the believes about the state variables are corrected with a linear combination (weighted average) of the predicted values and the measured values where the weights are given according to statistical properties. The idea of the Kalman filter algorithm is mainly based on the fact that linear transformations of Gaussian random variables result in other Gaussian variables and so it is only applicable for processes whose dynamical behavior can be modeled with linear differential equations.
To overcome this limitation, the most common adaptation of the Kalman filter algorithm to systems with nonlinear dynamics has been the so-called *extended Kalman Filter* (EKF). In the extended Kalman filter algorithm the prediction happens with the nonlinear system model but the coefficients for the update based on the original Kalman filter algorithm are determined with the Jacobian matrices (i.e. the first-order Taylor series approximation) of the (differentiable) nonlinear transformations. The EKF in general is not an optimal estimator but in many applications it has proven a good performance. On the other hand, in some cases it is difficult to implement and tune the filter. The filter may quickly diverge in cases of wrong initial state estimates and in system, which are highly nonlinear on the time scale of sampling [30].
The *unscented Kalman filter* (UKF) [31] applies a stochastic linearization method with the use of a weighted statistical linear regression process, which propagates more accurate mean and covariance information about the probability density than the first-order Taylor expansion of the nonlinear functions in the EKF. This linearization method is called the *unscented transformation* (UT).
The basic idea behind the UT is that one approximates the probability distribution instead of the nonlinear function. It uses a set of deterministically chosen weighted sigma points which represent the distribution. Out of these sigma points the characteristics of the distribution like the mean and the covariance can be computed. They are located pairwise and symmetrically along the main axes of the covariance and one point is located at the mean:

$$\chi^0 = \mu \tag{1a}$$

$$\chi^i = \begin{cases} \mu + \left(\sqrt{(n+\lambda)\Sigma}\right)_i & \text{for} \quad i = 1, \ldots, n \\ \mu - \left(\sqrt{(n+\lambda)\Sigma}\right)_i & \text{for} \quad i = n+1, \ldots, 2n \end{cases} \tag{1b}$$

where μ and Σ are the mean vector and the covariance matrix of the n-dimensional distribution, λ is a scaling parameter and $\left(\sqrt{(n+\lambda)\Sigma}\right)_i$ is the ith column of the matrix square root of the symmetric and positive definite $(n+\lambda)\Sigma$. For its calculation, the Cholesky decomposition is a numerically efficient and stable method.
The nonlinear function is applied to each sigma points and the mean and covariance after the transformation are estimated with a linear combination and a quadratic form of the results, respectively:

$$\mu' = \sum_{i=0}^{2n} w_m^i \Upsilon^i \tag{2a}$$

$$\Sigma' = \sum_{i=0}^{2n} w_c^i (\Upsilon^i - \mu')(\Upsilon^i - \mu')^T \tag{2b}$$

where the weights w_m^i and w_c^i can be given with the parameters α and β as:

$$w_m^0 = \frac{\lambda}{n+\lambda} \tag{3a}$$

$$w_c^0 = \frac{\lambda}{n+\lambda} + (1 - \alpha^2 + \beta) \tag{3b}$$

$$w_m^i = w_c^i = \frac{1}{2(n+\lambda)} \quad \text{for} \quad i = 1, \ldots, 2n \tag{3c}$$

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Υ^i is the result after the nonlinear transformation of χ^i:

$$\Upsilon^i = f(\chi^i) \tag{4}$$

The UKF algorithm consists of similar steps like the Kalman filter algorithm but the probabilistic believes are represented by the sigma points (instead of only the expected value and covariance of the normal distribution). The prediction steps need the use of the UT and in the update phase, the computation of the so-called Kalman gain has to be adapted to this belief representation. For the state-space model

$$x_{t+1} = f(x_t, u_t) \tag{5a}$$
$$y_t = h(x_t) \tag{5b}$$

the prediction steps read:

$$\chi_{t-1} = \begin{pmatrix}\mu_{t-1} & \mu_{t-1} + \gamma\sqrt{\Sigma_{t-1}} & \mu_{t-1} - \gamma\sqrt{\Sigma_{t-1}}\end{pmatrix} \tag{6a}$$
$$\bar{\chi}_t^* = f(\chi_{t-1}, u_t) \tag{6b}$$
$$\bar{\mu}_t = \sum_{i=0}^{2n} w_m^i \bar{\chi}_t^{*i} \tag{6c}$$
$$\bar{\Sigma}_t = \sum_{i=0}^{2n} w_c^i (\bar{\chi}_t^{*i} - \bar{\mu}_t)(\bar{\chi}_t^{*i} - \bar{\mu}_t)^T + R_t \tag{6d}$$
$$\bar{\chi}_t = \begin{pmatrix}\bar{\mu}_t & \bar{\mu}_t + \gamma\sqrt{\bar{\Sigma}_t} & \bar{\mu}_t - \gamma\sqrt{\bar{\Sigma}_t}\end{pmatrix} \tag{6e}$$
$$\bar{\Upsilon}_t = h(\bar{\chi}_t) \tag{6f}$$
$$\hat{y}_t = \sum_{i=0}^{2n} w_m^i \bar{\Upsilon}_t \tag{6g}$$

where $\gamma = \sqrt{n + \lambda}$ and R_t is the covariance matrix of the so-called *prediction noise* (also called *process noise*). The update steps are given as:

$$S_t = \sum_{i=0}^{2n} w_c^i (\bar{\Upsilon}_t^i - \hat{y}_t)(\bar{\Upsilon}_t^i - \hat{y}_t)^T + Q_t \tag{7a}$$
$$\bar{\Sigma}_t^{x,y} = \sum_{i=0}^{2n} w_c^i (\bar{\chi}_t^i - \hat{\mu}_t)(\bar{\Upsilon}_t^i - \hat{y}_t)^T \tag{7b}$$
$$K_k = \bar{\Sigma}_t^{x,y} S_t^{-1} \tag{7c}$$
$$\mu_t = \bar{\mu}_t + K_t(y_t - \hat{y}_t) \tag{7d}$$
$$\Sigma_t = \bar{\Sigma}_t - K_t S_t K_t^T \tag{7e}$$

Here Q_t is the covariance matrix of the *measurement noise*. For a more detailed description of the UKF algorithm see [31, 30, 7, 8].

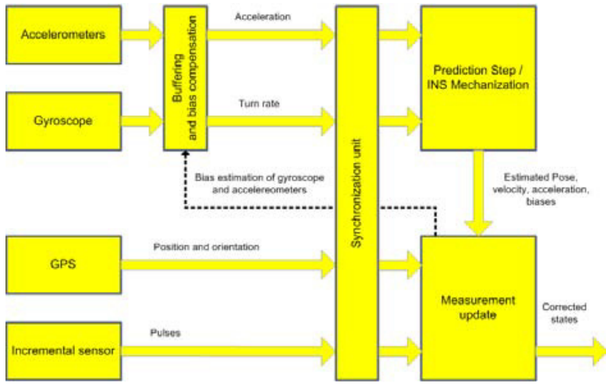

Figure 2: Localization system overview

4.2 UKF Localization System

The localization system which is depicted in Fig. 2 is implemented in a loosely coupled approach. This means that the whole system is divided into an inertial navigation system (INS), which provides the data for the UKF pose predictions and a correction block consisting of the GPS unit and an incremental sensor. The system state vector

$$X = \begin{bmatrix} x & y & v_x & v_y & \Theta & b_{a_x} & b_{a_y} & b_g \end{bmatrix} \tag{8}$$

consists of the vehicle's lateral direction (x), the vehicle's longitudinal direction (y), the corresponding velocities (v_x and v_y), the orientation (Θ) and the biases for the accelerometers (b_{a_x}, b_{a_y})and the gyro bias (b_g). During the start-up phase of 15 seconds the initial biases of the gyro and the accelerometers are determined and set for error compensation. Additionally the initial orientation is set which comes from the GPS system as no other absolute orientation sensor is available. After the initializing phase the INS provides data with a rate of 10 Hz. All incoming INS data is firstly band limited, bias corrected and buffered to get a rate scalable system. When the UKF prediction is triggered by the synchronization layer, the filtered INS sensor data in terms of turn rate (θ_k) and accelerations in lateral (a_{x_k}) and longitudinal (a_{y_k}) directions are used as input to calculate a new UKF state prediction for the interval δt. This process of aligning the body frame to the navigation frame by utilization of the turn rate and double integration of the acceleration yielding in a new pose estimation is often called the INS mechanization:

$$\Theta_{k+1} = \Theta_k + \theta_k \delta t \tag{9a}$$
$$C = \cos(\Theta_{k+1}) \tag{9b}$$
$$S = \sin(\Theta_{k+1}) \tag{9c}$$
$$\delta v_y = \left[C(a_{y_k} - b_{a_{y_k}}) + S(a_{x_k} - b_{a_{x_k}})\right] \delta t \tag{9d}$$
$$\delta v_x = \left[-S(a_{y_k} - b_{a_{y_k}}) + C(a_{x_k} - b_{a_{x_k}})\right] \delta t \tag{9e}$$
$$v_{y_{k+1}} = v_{y_k} + \delta v_y \tag{9f}$$
$$v_{x_{k+1}} = v_{x_k} + \delta v_x \tag{9g}$$

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$$x_{k+1} = x_k + v_{x_k}\delta t + \delta v_x \frac{\delta t^2}{2} \quad (9h)$$

$$y_{k+1} = y_k + v_{y_k}\delta t + \delta v_y \frac{\delta t^2}{2} \quad (9i)$$

$$b_{a_{x_{k+1}}} = b_{a_{x_k}} \quad (9j)$$

$$b_{a_{y_{k+1}}} = b_{a_{y_k}} \quad (9k)$$

$$b_{\theta_{k+1}} = b_{\theta_k} \quad (9l)$$

Due to the small operational area, the limited computational power and the low cost INS sensors a sophisticated error compensation as described in [1] can be neglected [2].

To update the state estimation two methods are implemented. If GPS is available the incoming GPS data triggers the UKF update and the state is corrected by the GPS position and orientation, while velocity comes from the incremental sensor. The used output is given in equation (10) where lever arm compensation terms are neglected, as the GPS unit is directly attached above the INS unit. The corrected pose is stored afterwards.

$$y = y_{GPS} \quad (10a)$$

$$x = x_{GPS} \quad (10b)$$

$$v_{INC} = \sqrt{v_x^2 + v_y^2} \quad (10c)$$

$$\Theta = \Theta_{GPS} \quad (10d)$$

If GPS outages occur, the UKF pose correction is triggered by the synchronization layer. In this case the correction data is calculated for the correction interval δt from the stored pose, the turn rate (θ_k) and the velocity (v_k) from the incremental sensor utilizing the kinematic model given in 11.

$$X_{k+1} = X_k + v_k \cdot \sin\Theta_k \cdot \delta t \quad (11a)$$

$$Y_{k+1} = Y_k + v_k \cdot \cos\Theta_k \cdot \delta t \quad (11b)$$

$$\Theta_{k+1} = \Theta_k + \theta_k \delta t \quad (11c)$$

The implementation of the alternative correction method enables a permanent correction of the state estimation and attenuates the typical INS drift during GPS outages. For an optimal covariance weighting in each update step the covariances are dynamically adapted in correspondence to the actual speed or GPS variance values [32].

5 Experiments

In order to prove the performance of the sensor fusion algorithm described in Subsection 4.2, we performed indoor as well as outdoor measurements. The most important difference between the indoor and outdoor test environments is in the absence and presence of the GPS measurement data, respectively. Another important difference arise from flatness of the ground. Indoor tests take place in the robotics hall of the University of Würzburg. The surface in the hall is particular plane compared to the rough outdoor test area, which induce a lot of noise to the system. On the other hand, the GPS measurements in the outdoor environment prevent the positioning from accumulating the measurement errors by integration that is a well-known effect in dead-reckoning techniques. But in the outdoor environment the variance of the GPS measurements is obviously an upper bound for the position estimates.

The results of the sensor fusion in the indoor tests are validated with a high precision tracking system that is described in Subsection 5.1. The succeeding subsection gives detailed results about the indoor tests and Subsection 5.3 presents the results of the outdoor experiments, where the trajectory, which was obtained with the sensor fusion algorithm, are compared with the GPS measurements.

5.1 High Precision Localization System for Validation

We validated the above presented sensor fusion algorithm in the indoor tests with the help of the iSpace positioning system that is a high-precision metrology and tracking product of Nikonmetrology [33]. This system consists of six transmitters, each placed onto a tripod, wireless sensor frames and a base station that receives data from the wireless sensor frames and computes their position. The iSpace positioning system is an active laser-based metrology system. The rotating heads of the transmitters emit two fan-shaped laser beams at right angles with a working range between 2 and 55 meters. Each transmitter is adjusted to a unique frequency of rotation and covers the surrounding area with a vertical opening angle of $40°$. The wireless sensor frames consist of at least one detector, a photo diode with a horizontal opening angle of $360°$ and a vertical opening angle of $90°$, and a radio frequency (RF) communication module for a data link to the base station. The use of more then one detector increases the accuracy of the positioning due to the redundant measurements. If several detectors are used, the accurate position of each detector is needed in a coordinate system fixed to the sensor frame and this setup of detectors has to be registered at the base station. The number of detectors on a frame also determines the number of the detectable rotational degrees of freedom in the positioning. In order to be able to measure all six degrees of freedom of the rigid frame (the three translational and three rotational degrees of freedom), at least three detectors are needed.

The base station calculates the elevation and azimuth angles between sensors and each visible transmitter. The two angles define a straight line from transmitter to sensor. The length of the lines are determined by triangulation. Therefore the knowledge about the location of the transmitters relative to each other is necessary. This is done by the semi-automatic bundling process where a special wireless sensor, the 2 m long scale bar has to be carried around the whole measurement volume. With the help of the recorded data the system determines the relative posi-

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tion of the transmitters by dint of an optimization process. This process also determines a coordinate system for the positioning but its orientation and the position of its origin is a result of the bundling process and they are not defined previously. However, an additional reference frame can be defined and the position coordinates of the measurements can automatically be transformed into this coordinate system. The global measurement uncertainty of the iSpace system depends on the environment, the system setup and the sensor frames. For typical setups, an uncertainty of 0.25 mm can be achieved. The sampling rate of the wireless frames is approximately 40 Hz. Though due to the necessary processing time for calculating the position, this data rate is only applicable for off-line analysis.

5.2 Indoor Experiments

In order to record the path traveled by the mobile robot, the iSpace measurement system described in the previous subsection was set up in a test hall. The transmitters were placed roughly on the boundary of a virtual ellipse with a major axis of about 14 m and a minor axis of about 8 m. As the relative position of the transmitters is computed during a bundling process there is no need of a precise setup. A calibrated wireless sensor frame was attached to the mobile robot, which includes two so-called mini vector bars with accurately measured pose on the frame. Each of the mini vector bars consists of two detectors and so four sensors are used for the positioning of the robot (note the redundancy). The measurements were transformed into a coordinate system, where the x-y plane is aligned to the floor of the test hall. During the tests the Outdoor MERLIN mobile robot did not leave the operation volume of iSpace.
The aim of the indoor tests was to analyze the performance of the sensor fusion algorithm in the case when no GPS measurements are available. The main problem in this case is the integration of the noisy measurements because even a small DC offset error corrupt the result after a long integration time. This effect is well-known and understood from odometry and dead-reckoning methods. Our algorithm achieves the fusion of acceleration data of the INS and velocity data obtained from the incremental encoder on the motor shaft and from the gyroscope (yaw rate).
In Figs. 3-5 three different indoor test scenarios are presented. The test scenarios distinguish in the trajectories. All three figures show the curves obtained from the sensor fusion algorithm as well as the curves registered with the iSpace metrology system. Fig. 3 shows a relatively straight trajectory and the driven arc in Fig. 4 has a smooth curvature while the S-curve test in Fig. 5 include some parts with maximal steering. Observe that generally the positioning error increases with time but the main error component is in the lateral direction and this error seems to depend on the steering direction. The final errors are between 15 cm and 30 cm that correspond to the low-cost components of the Outdoor MERLIN mobile robot.

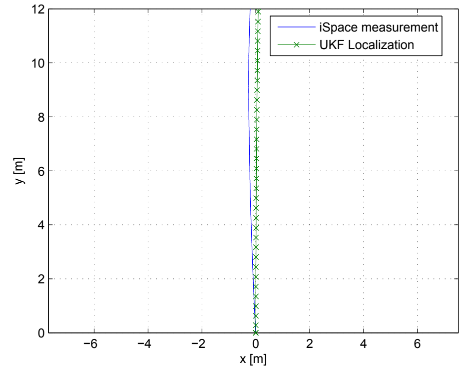

Figure 3: Indoor test with a straight path

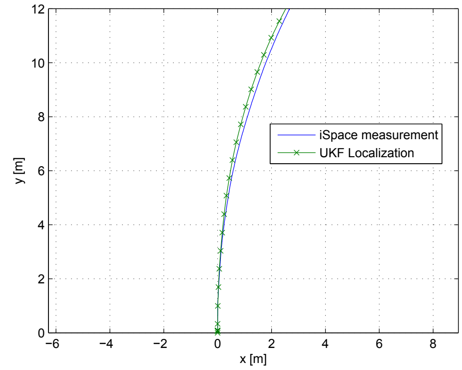

Figure 4: Indoor test with a modest curvature path

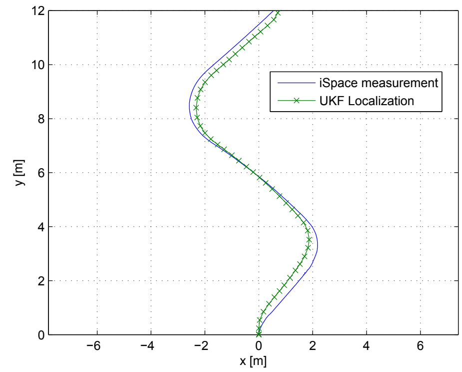

Figure 5: Indoor test with an S-curve path

5.3 Outdoor Experiments

The outdoor tests took place on the special outdoor test area for mobile robots located at the University of Würzburg. The test area includes different surfaces like hills, obstacles, pipe lines and rough grassland. During the outdoor tests, the rover was remotely navigated over all surfaces, but mainly over rough grassland. The uneven,

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bumpy ground affects especially the INS performance by inducing increased disturbances to the system.

During the outdoor tests the UKF prediction is corrected by the GPS pose data in combination with the incremental sensor as described in section 4.2. Fusing the INS with absolute global values prevents the increase of the dead reckoning errors. Due to the rough ground the overall performance mainly depends on the GPS reception quality. The GPS fix quality of the integrated GPS receiver, can be improved by activating the SBAS option [5]. Additionally the GPS receiver supports different kinds of speed modes. Therefore the pedestrian mode was chosen as it fits the best to the speed profile of the MERLIN robot. Finally a maximum HDOP value of 10 was set and only GPS fixes with at least 4 satellites were accepted.

Based on these GPS settings several test runs with different trajectories have been done. Figure 6 shows one example of the UKF positioning algorithm results during the outdoor tests. The picture shows the GPS fixes and the corresponding corrected UKF results. The average overall positioning error during the circle test drives with an approximate track length of 100 meters is beneath 1.5 meter.

It can be observed that due to the chosen settings the GPS fixes have a good quality and correlate quite good to the actual driven course. In general neither outliers nor bigger GPS jumps could be observed during the outdoor tests. The variance of the GPS receiver was in general 2 meters and the correction process was weighted accordingly.

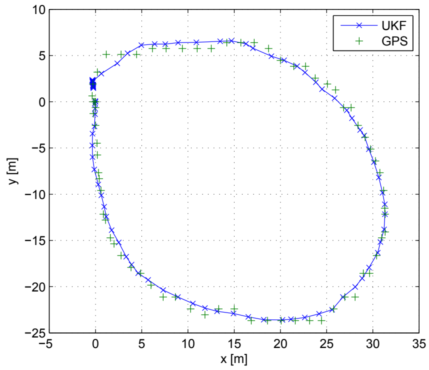

Figure 6: Performance in outdoor evironment

Further improvements relating the filter performance will be done by exchanging the low cost INS sensors by more accurate ones. Besides that the integration of a compass will help to determine and correct the orientation more precisely right from the start yielding more accurate pose calculations. For short term operations one can consider to remove the slow varying biases from the state vector to reduce the sigma point amount. By predefining them more resources can be given to other applications in the operating system.

6 Conclusion

In this paper a new UKF variant is described to fuse inertial sensor and GPS data yielding the global position of the small sized robot called Outdoor MERLIN. The whole localization system was implemented on a 20 MHz microcontroller and integrated to the Outdoor MERLIN operating system. The alternative update strategy with the corresponding variance adaption allows continuous UKF corrections even during GPS outages or in indoor environments. To verify the performance of the filter the high precision localization system iSpace was used which revealed the capabilities of the UKF and the chosen loosely coupled approach. Especially the permanent correction attenuates the typical INS drift during GPS outages and in turn corrects the relatively inaccurate low cost accelerometers. The performance in outdoor environments is mainly dependent on the quality of the GPS fixes. By accounting the integrated filter capabilities of the GPS receiver in terms of pedestrian mode, activated SBAS, a HDOP limit of 10 and at least 4 satellites guarantees optimal outdoor results. Future experiments investigating the performance of the alternative correction method during longer GPS outages and in harsh outdoor environment by utilizing the iSpace system will follow.

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