A New Pedestrian Navigation Algorithm Based On The Stochastic Cloning Technique For Kalman Filtering

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ABSTRACT

In this paper we present a pedestrian navigation algorithm based on a Kalman filter that exploits relative position measurements provided by a step detection algorithm.
In the development of pedestrian navigation systems we face certain challenges. In particular, GPS is often temporarily unavailable, especially in urban application scenarios. In addition, the sensor equipment has to be comfortably wearable by humans and is therefore constrained concerning its weight. For a broad application the cost of the overall sensor system is also a major concern. A common approach to meet these requirements is to exploit a low-cost IMU built with MEMS-technologies and additional sensors like a barometric altimeter and a magnetometer in order to estimate the position of the pedestrian when GPS is not available. Because the measurements from MEMS-IMUs are corrupted by substantial noise and biases, a direct integration of sensor readings provides a suitable position and orientation estimate only for a very limited period of time, typically a few seconds. One approach to alleviate these problems is to apply a technique called pedestrian dead reckoning where the orientation estimate is used to determine the direction of a step. The position estimate is obtained afterwards by concatenating the estimates of relative movement resulting from each step. In this two-step approach to pedestrian navigation there is no estimate of the joint distribution over position and orientation available. Therefore the correlations between them cannot be exploited during the estimation process. This aggravates sensor fusion in the case that additional measurements from exteroceptive sensors or GPS measurements become available.
Therefore we propose to use a technique known as "stochastic cloning" to enable a direct integration of the relative position measurements arising from detected steps in a Kalman filter whose state vector comprises all relevant state variables. The main advantage of this approach is a correct treatment of the uncertainties arising from the delta measurements thus enabling accurate weighting of the state variables during sensor fusion with exteroceptive sensors or GPS.

INTRODUCTION

Pedestrian Navigation is a field of intensive study for many years now. One possible application is to support mission control for security forces or first responders. For this purpose a reliable estimate of the position of staff members is needed even under difficult conditions. In urban areas multipath effects and occlusions due to high buildings regularly impede the usage of GPS or related satellite navigation technologies. Similarly satellite navigation is not available for indoor applications. Furthermore a pedestrian navigation system used for instance by first responders should not rely on special infrastructure like fiducial markers which had to be deployed in advance of an emergency. A navigation system that is supposed to support its users to orient themselves in previously unknown environments should also be capable of recording a map of the explored area. This in turn necessitates the use of exteroceptive sensors, which provide information about the environment, like cameras or laser scanner.

An overview of algorithms commonly applied to this simultaneous localization and mapping (SLAM) problem is given in [1]. These algorithms typically combine measurements from exteroceptive sensors with robot odometry information using Bayesian filtering techniques. However, a direct adaptation of these techniques to the problem of pedestrian navigation is difficult due to the highly dynamic motion of pedestrians. Since robot motion is typically restricted to a plane, three parameters are usually sufficient to describe position and orientation of a robot. Wheel encoders yield accurate estimates of robot motion between consecutive measurements of the environment.

One way to deal with the high dynamics of human motion is to use a parameterization that takes into account all six degrees of freedom for position and orientation and to exploit measurements from accelerometers and gyroscopes to calculate estimates of relative motion between exteroceptive sensor measurements. Veth and Raquet choose this approach for their SLAM system [2]. They combine inertial measurements with measurements from a monocular camera using an EKF. The problem of scale drift in monocular slam is addressed by initializing new features using a stereo rig or a terrain model. The advantage of this approach is that it does not require a domain specific motion model and can thus be employed for aircraft navigation as well as indoor navigation of pedestrians or mobile robots. However it would be highly beneficial if the scale information was determined reliably by the IMU's accelerometers measurements. This might be accomplished by exploiting the length information inherent in human steps.

Several pedestrian dead reckoning systems have been developed which combine a torso mounted IMU with a magnetometer by simply concatenating displacement estimates calculated from the estimated step length and compass heading, cf. [9],[10]. Step detection algorithms are generally based on acceleration measurements and a step model. One of the most advanced models was introduced by Kim et al. [9]. For most of the scenarios the accuracy of torso mounted systems is better than 5% of the traveled distance and the main source of error is the magnetic disturbance.

Robertson et al. have proposed a localization and mapping system for pedestrians that relies solely on measurements of a foot mounted IMU, which is used to detect steps and position displacements using zeros velocity updates [3]. The path is represented by transition probabilities between hexagonal cells, which constitute a subdivision of the ground plane.

A system combining measurements from a 2D-laser scanner with inertial measurements was presented by Ascher et al. [4]. Whenever a step is detected, a new position estimate is calculated by adding a vector that describes the motion due to the step to the position of the system at the beginning of that step. The new position estimate is used thereafter to update a filter which estimates the pose of a torso-mounted IMU and a map of orthogonal line segments extracted from the laser scans. This setup enables tight integration of the torso-mounted IMU with exteroceptive sensors, but it does not fully reflect the relative nature of the measurements.

A theoretically sound technique to process relative pose measurements within a Kalman filter was introduced by Roumeliotis and Burdick for the case of a robot moving in a plane with three DOF [5]. The general idea is to augment the Kalman filter state with the robot's pose at the beginning of the relative movement. Hence this technique is called "stochastic cloning" by the authors. Whenever a relative pose measurement is made, it can be expressed in terms of the current pose and the previous pose in the measurement equation for the Kalman filter. The authors provide Monte Carlo simulation results indicating that their approach outperforms simple concatenation of relative pose measurements. The approach was later extended to 6 DOF relative pose measurements [6].

MULTI-SENSOR FUSION FOR PEDESTRIAN NAVIGATION

An overview of the concept for combining the information of multiple sensors in the context of pedestrian navigation employed in this work is given in Fig. 1. The high frequency of inertial measurements from accelerometers and gyroscopes precludes their usage as ordinary measurements to update the state of the extended Kalman filter, which is used to estimate position and orientation of the sensor system. Instead, they are directly processed by the strapdown algorithm, which propagates the current state estimate in time and calculates an estimate of its uncertainty in form of a covariance matrix. Whenever a new measurement from one of the additional sensors arrives, an EKF measurement update is performed to correct the errors in the current state estimate. The correlations expressed by the off-diagonal terms of the covariance matrix describe how distinct state entries are related. They afford the estimation of parameters which cannot be directly measured but may nonetheless have a strong influence on the estimated state, e.g. the biases which corrupt IMU measurements. Thus the correlations provide valuable information which cannot be exploited if the estimation of orientation and position are separated.

Magnetometers permit the estimation of the yaw-angle, which defines the heading of the pedestrian. In this work the complete normalized measured magnetic field vector is used to update the filter. Since the magnetic field is sensitive to ferromagnetic materials in the proximity a large measurement uncertainty is assumed when updating the filter. In addition, the deviation from the expected norm of the magnetic field can be used to detect ample measurement errors.

A barometric altimeter is employed to measure the height of the sensor system with respect to the initial position and GPS measurements are incorporated if available.
The filter state vector may be augmented with a map containing the positions of landmarks observed by exteroceptive sensors. The resulting SLAM system provides the user with a map of the explored environment.
The following sections describe how relative position measurements provided by a step detection algorithm can be integrated in this filter setup.

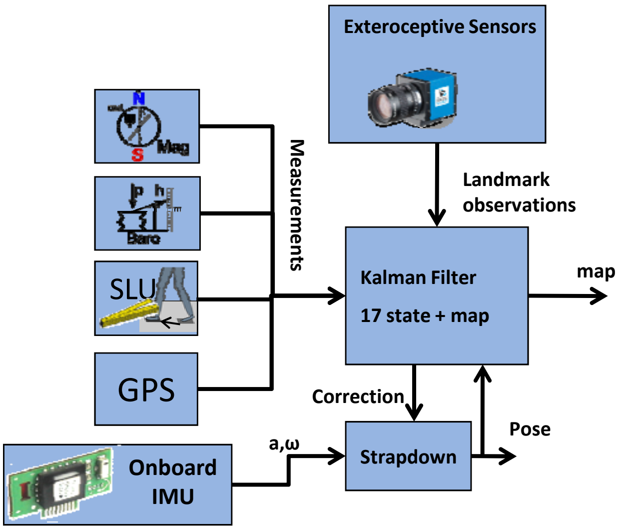

Fig. 1: Overview of the multi-sensor fusion concept for pedestrian navigation presented in this work.

STEP DETECTION

A crucial factor for many pedestrian navigation systems is the robustness of step detection. We propose the use of acceleration data in down and forward direction. The step events are located by searching for local minima in the acceleration signal under a given threshold during a defined time window. With this algorithm, steps can be detected by a probability of 98-99% but still errors occur in the following cases:

- First step of a walk after stand still yields to low acceleration peaks which are hard to detect
- Stairs: the acceleration peaks are smaller due to lower velocities at the end of the step on the next stair
- Slow walks

Consequently the step detection is extended to an adaptive, two-staged threshold which is demonstrated in Fig. 2.
Two thresholds are used: A step is detected if an already detected negative down acceleration peak is under the lower threshold. If it's between the two thresholds, the forward acceleration peak also needs to be higher than a defined value to confirm a step.
The thresholds are adapted to the energy (signal variance) of the acceleration signal during the last foot step. Finally the time window between 2 steps must be higher than a minimal step time length. If this is not the case, the down acceleration minimum with the more significant peak will be detected as a step.
With this adaptive, two-staged threshold our step detection is robust in any situation of a pedestrian walk.

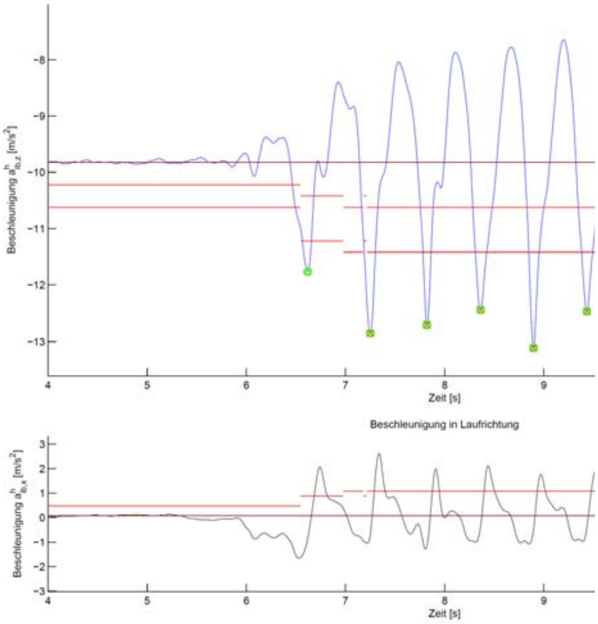

Fig. 2: Adaptive two-staged threshold for acceleration peaks in down direction and additional adaptive threshold for forward direction.

STATE PARAMETERIZATION

In this work we have adopted the error space formulation of the EKF used for GPS-INS integration by Wendel [7]. The EKF is employed to estimate the deviation between the parameter estimates and their true values. When used for GPS-INS integration, the state vector typically comprises position, velocity, orientation and the IMU's biases.
The step detection algorithm described in the previous section is employed to detect the completion of a step. We assume that the step length is almost constant and the direction of movement is coincident with the forward direction at the beginning of the step as shown in Fig. 3. Thus, the detection of a step contains information about the displacement of the pedestrian and the attached sensor system in the horizontal plane. In order to process these displacement measurements the state vector of the aforementioned Kalman filter is extended with the position of the pedestrian at the beginning of a step. Therefore the state vector is given by:

$$\mathbf{x}_t = \begin{bmatrix}\mathbf{y}^T & \mathbf{p}_c^T\end{bmatrix}_t^T = \begin{bmatrix}\mathbf{p}^T & \mathbf{v}^T & \mathbf{b}_a^T & \mathbf{q}^T & \mathbf{b}_g^T & \mathbf{p}_c^T\end{bmatrix}_t^T$$

Where $\mathbf{y}$ summarizes the parameters describing the IMU's motion and $\mathbf{p}_c$ is the cloned position of the sensor system at the beginning of the current step in the horizontal plane. Position $\mathbf{p}$ and velocity $\mathbf{v}$ of the IMU are given in coordinates of the navigation frame {n}, whose z- and x-axis are aligned with the direction of local gravity and the north direction respectively. The quaternion $\mathbf{q} = \mathbf{q}_b^n$ describes the rotation between the IMU's coordinate frame {b} and the navigation frame. It is presumed, that the navigation frame is constant over time. Furthermore, $\mathbf{b}_a$ and $\mathbf{b}_g$ contain the biases which corrupt the IMU's acceleration and angular velocity measurements.
In the following, a preceding Δ is used to denote the errors in the state estimates:

$$\begin{aligned}\Delta\mathbf{x}_t &= \begin{bmatrix}\Delta\mathbf{y}^T & \Delta\mathbf{p}_c^T\end{bmatrix}_t^T \\ &= \begin{bmatrix}\Delta\mathbf{p}^T & \Delta\mathbf{v}^T & \Delta\mathbf{b}_a^T & \Delta\mathbf{\Psi}^T & \Delta\mathbf{b}_g^T & \Delta\mathbf{p}_c^T\end{bmatrix}_t^T\end{aligned}$$

Where $\Delta\mathbf{x}_t$ is the error state that is actually estimated by the filter. The Rodrigues vector $\Delta\mathbf{\Psi}$ describes the incremental rotation between the true orientation and its estimate.
In the following it will be helpful to consider the subsequent partitioning of the state vector which highlights the position in the horizontal plane and its cloned counterpart:

$$\mathbf{x}_t^T = \begin{bmatrix}\mathbf{p}_\perp^T & \mathbf{w} & \mathbf{p}_c^T\end{bmatrix}_t^T \quad (*)$$

Here, $\mathbf{p}_\perp$ is the current position in the horizontal plane and $\mathbf{p}_c$ is the position at the beginning of the last step.

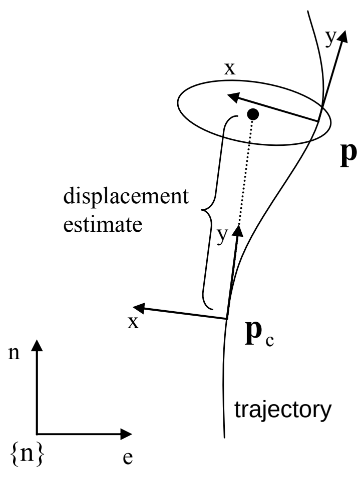

Fig. 3: Definition of the displacement estimate in the horizontal plane.

TIME UPDATE

During the time update, the state estimate and the covariance of the error state are propagated through the process model using the measurements of the IMU. New IMU measurements are corrected with current bias estimates and subsequently integrated. Angular rate measurements are integrated by multiplying the quaternion corresponding to the current orientation estimate with the incremental rotation quaternion formed with the angular rate measurements. For the integration of the position estimate, the acceleration measurements are first transformed to the navigation frame with the current orientation estimate. Then the gravitational acceleration is subtracted and the resulting acceleration estimate with respect to the fix navigation frame is used to calculate new estimates for velocity and position.
The part $\Delta\mathbf{y}$ of the error state vector, which contains the errors in the parameter vector without the cloned position, is propagated according to a first order differential equation:

$$\Delta\dot{\mathbf{y}} = \mathrm{F}_y\,\Delta\mathbf{y} + \mathrm{G}_y\mathbf{n}$$

Matrix F_y in the above equation is determined by the physical model which underlies the integration of the IMU's measurements. Noise terms and their effects on the error state are modeled by vector $\mathbf{n}$ and Matrix G_y. Here, uncorrelated, white noise is assumed.
From matrix F_y the discrete time transition matrix Φ_y is computed for each IMU measurement:

$$\Phi_y = \exp(\mathrm{F}_y \cdot \tau) \approx \mathrm{I} + \mathrm{F}_y \cdot \tau$$

Where τ stands for the constant time between two consecutive IMU measurements. Typically, there are several IMU measurements between consecutive measurements from exteroceptive sensors or step length updates. Therefore, the transition matrix between filter updates is obtained by multiplying the individual transition matrices corresponding to intermediate IMU measurements:

$$\mathrm{A}_{y,t} = \prod_{i=0}^{k-1}\Phi_{y,t+i}$$

Consequently, $\mathrm{A}_{y,t}$ is the discrete time transition matrix between measurements at time t and t+k for the reduced error state.
The term "stochastic cloning" stems from the manipulation of the filter state whenever a displacement has been processed. On this occasion, the estimate of the position in the horizontal plane is copied from $\mathbf{p}_\perp$ to $\mathbf{p}_c$ and the covariance matrix of the complete error state vector is adapted accordingly:

$$\mathbf{x} = \begin{bmatrix} \mathbf{p}_{\perp}^{T} & \mathbf{w}^{T} & \mathbf{p}_{\perp}^{T} \end{bmatrix}^{T}$$

$$P_{\Delta x \Delta x} = \begin{bmatrix} P_{\Delta \mathbf{p}_{\perp} \Delta \mathbf{p}_{\perp}} & P_{\Delta \mathbf{p}_{\perp} \Delta \mathbf{w}} & P_{\Delta \mathbf{p}_{\perp} \Delta \mathbf{p}_{\perp}} \\ P_{\Delta \mathbf{w} \Delta \mathbf{p}_{\perp}} & P_{\Delta \mathbf{w} \Delta \mathbf{w}} & P_{\Delta \mathbf{w} \Delta \mathbf{p}_{\perp}} \\ P_{\Delta \mathbf{p}_{\perp} \Delta \mathbf{p}_{\perp}} & P_{\Delta \mathbf{p}_{\perp} \Delta \mathbf{w}} & P_{\Delta \mathbf{p}_{\perp} \Delta \mathbf{p}_{\perp}} \end{bmatrix}$$

In the course of the cloning procedure, the current orientation quaternion is copied to the quaternion $\mathbf{q}_{b,c}^{n}$, which describes the orientation of the sensor system at the beginning of the new step. However, the cloned orientation is not part of the filter state and therefore does neither appear in the state vector nor in the covariance matrix.
The cloned position is static: It does not change in time. Thus the discrete time transition equation between filter updates at time t and t+k is given by:

$$\begin{bmatrix} \Delta \mathbf{y} \\ \Delta \mathbf{p}_{c} \end{bmatrix}_{t+1} = \underbrace{\begin{bmatrix} A_{y,t} & 0 \\ 0 & I \end{bmatrix}}_{A_{\mathbf{x},t}} \begin{bmatrix} \Delta \mathbf{y} \\ \Delta \mathbf{p}_{c} \end{bmatrix}_{t} + \underbrace{\begin{bmatrix} \mathbf{w}_{y,t} \\ 0 \end{bmatrix}}_{\mathbf{w}_{\mathbf{x},t}}$$

The covariance matrix of the augmented state is propagated according to the following equation:

$$P_{\Delta \mathbf{x} \Delta \mathbf{x}, t+k} = A_{\mathbf{x},t} P_{\Delta \mathbf{x} \Delta \mathbf{x}} A_{\mathbf{x},t}^{T} + Q_{x,t}$$

Where $Q_{\mathbf{x},t}$ is the covariance matrix of the process noise vector $\mathbf{w}_{\mathbf{x},t}$.

MEASUREMENT UPDATE

Each time the completion of a step is detected, a step length update is performed. In the coordinates of the sensor coordinate system at the beginning of the step, when the position estimate has been cloned, an estimate of the displacement vector can be calculated:

$${}^{b}\mathbf{d} = \alpha \cdot \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}^{T}$$

Here, α is the step length and ${}^{b}\mathbf{d}$ is the calculated displacement measurement in the coordinates of {b}. The corresponding measurement equation expresses the displacement vector in terms of the position in the navigation frame ${}^{n}\mathbf{p}_{1}$ at the beginning and the position ${}^{n}\mathbf{p}_{2}$ at the end of a step:

$${}^{b}\mathbf{d} = C(\mathbf{q}_{b,c}^{n})^{T} ({}^{n}\mathbf{p}_{2} - {}^{n}\mathbf{p}_{1}) + \mathbf{v}$$

Where $C(\mathbf{q})$ denotes the rotation matrix associated with quaternion $\mathbf{q}$ and $\mathbf{v}$ is the measurement noise with covariance matrix R. In the above equation, the relative position estimate depends on the orientation of the sensor system belonging to the cloned part of the state. Since this orientation estimate is not part of the filter state it is presumed to be constant and is used to calculate a displacement estimate in the coordinates of {n} in the horizontal plane that can be directly applied as a displacement measurement, hence facilitating the formulation of the measurement equation. For this purpose, the direction of the step w.r.t. frame {n} is extracted from $C(\mathbf{q}_{b,c}^{n})$, projected on the horizontal plane, and finally normalized so that its length in the horizontal plane matches the step length. With the resulting two-dimensional relative position estimate ${}^{n}\mathbf{d}_{\perp}$ the measurement equation becomes:

$${}^{n}\mathbf{d}_{\perp} = \mathbf{p}_{\perp} - \mathbf{p}_{c} + \mathbf{v}$$

Thus the measurement matrix H corresponding to the state partitioning (*) is given by:

$$H = \begin{bmatrix} I_{2\times2} & 0_{2\times13} & -I_{2\times2} \end{bmatrix}$$

The measurement covariance matrix R describes deviations between the calculated relative position measurement and the true motion due to variations in gait and further unmodeled effects. The experiments presented in the next section were conducted with an assumed standard deviation of 5 cm in walking direction and 25 cm in lateral direction.
Finally, the derived displacement measurement and the corresponding measurement matrix H are employed to perform an EKF update.
Note that the approach in this paper differs from the stochastic cloning technique introduced in [5] in two points: (1) This work is restricted to relative position measurements in the horizontal plane. In particular, the orientation of the system at the beginning of a step is neglected. (2) The condition that the relative position measurement should not alter the previous position in the cloned part of the state vector is not enforced.

MONTE CARLO SIMULATION

A number of monte carlo simulations were run on a simulated trajectory. The simulations provide a way to investigate the behavior of the filter and to evaluate the performance of the proposed method with regard to alternative techniques by comparing the estimated trajectories with the ground truth. During each monte carlo run three position estimates were calculated separately with the following techniques: (1) the stochastic cloning approach (SC SLU) described in this work (2) pseudo position measurements (PP SLU) to update the Kalman filter (3) pedestrian dead reckoning (PDR). For the pseudo position measurements, an estimate of the current position in the horizontal plane is calculated from the orientation estimate at the beginning of the step in the same fashion as the calculation of the displacement measurement shown in Fig. 3. During the pseudo position measurement update, the measurement covariance matrix used for displacement measurements in the SC SLU is adapted by adding a multiple of the trace of the estimated position's covariance matrix to all of its diagonal entries. The resulting covariance matrix is used as measurement covariance matrix in the pseudo position filter update thereby taking into account the growing position estimate error during pseudo position updates.

Fig. 4 presents the error with associated 3σ covariance bounds for the three approaches averaged over 100 monte carlo runs. The outcome of one particular test run is shown in Fig. 5.

While the stochastic cloning approach yields results which are comparable to pedestrian dead reckoning, it significantly outperforms pseudo position updates. More importantly, the error is within the 3σ-bounds of the estimated covariance most of the time. As one would expect when employing relative position measurements, the uncertainty of position increases monotonically. In contrast the estimated uncertainty even declines when employing pseudo position measurements, although the uncertainty of the position estimate is considered during the update. Note, that the pedestrian dead reckoning approach does not provide a measure of uncertainty of the position estimate at all.

The next section describes how the ground truth trajectory used for the evaluation was generated. After that, results for real data will be discussed.

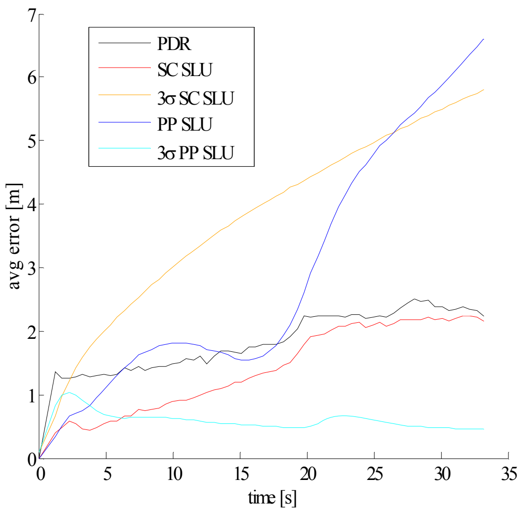

Fig. 4: Error and 3σ-bounds for different pedestrian navigation approaches averaged over 100 monte carlo runs with the simulated trajectory also shown in Fig. 5.

Two C^2 splines are employed to define reference trajectories. One spline determines the viewing direction while the other spline describes the position of the IMU. The acceleration measurements are generated from the second derivative of this spline. Angular velocity measurements are derived from the differential rotation between two sampling points. Before each monte carlo run artificial white noise and random biases are individually added to the acceleration and angular rate measurements. Biases are constant during monte carlo runs. The variance of the artificial noise was identified by measurements with the real IMU used for the experiments which are described in the next section. In addition barometric altimeter and magnetometer measurements are generated. In order to simulate the sinusoidal up and down movement that is typical for human steps the spline control points were accordingly shifted in the vertical direction. Also deviations from gait pattern are simulated by adding noise to the spline control points. The resulting trajectory offers a rough approximation of human motion. However it is sufficient for the step detection algorithm described earlier in this paper to detect all simulated steps in the artificial trajectory. Therefore the same algorithm can be used to evaluate real as well as simulated trajectories.

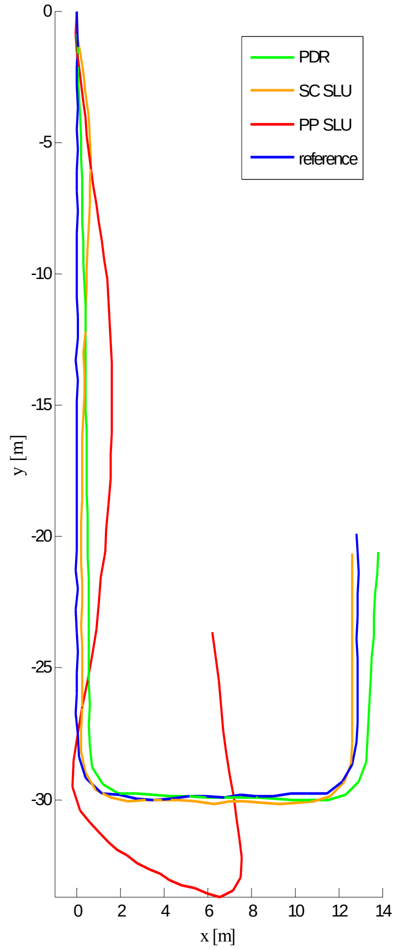

Fig. 5: Outcome of one monte carlo run for different pedestrian navigation algorithms.

REAL DATA EXPERIMENT: GPS INTEGRATION

Figures Fig. 6 and Fig. 7 demonstrate the performance of the different methods for pedestrian navigation on a mixed outdoor and indoor dataset. The trajectory starts on a public street, where a good quality GPS signal is available. However, the quality of the GPS-signal quickly declines in the proximity of the large office building, probably due to multipath effects. The true trajectory enters the building on the right side wing and then follows the hallway that is also shown in Fig. 6. This hallway is all straight except for one turn where the side wing meets the central aisle. During the walk through the building, the GPS signal is completely lost. It recovers when the trajectory leaves the building. However, it is disturbed so that the GPS measurements suggest a position inside the building while the true trajectory proceeds in front of the building to the right. At the end of the trajectory the quality of the GPS signal increases with the distance to the building therefore providing a good estimate of the position again.

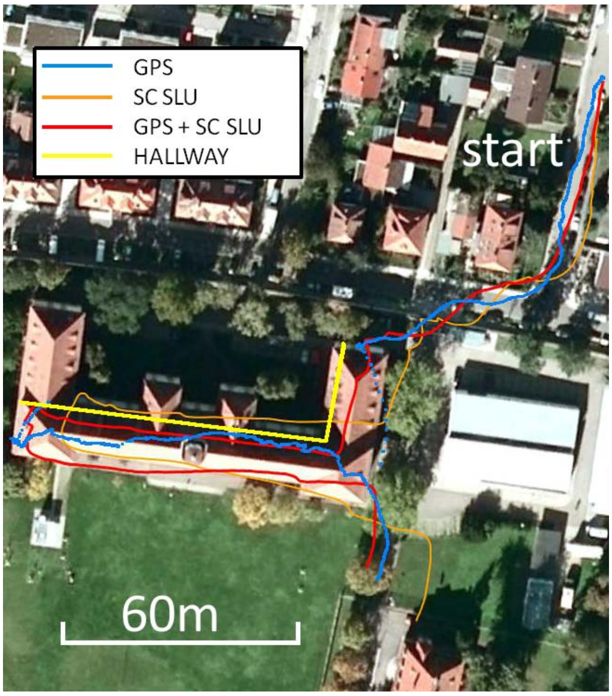

Fig. 6: Performance of the SC SLU algorithm on a mixed outdoor and indoor dataset with and without GPS aiding.

The SC SLU and the PP SLU were applied to this dataset both with and without updating the filter with GPS measurements. Obviously, the SC SLU approach benefits from GPS updates, as the estimated trajectory reflects the true trajectory well if both are combined. In contrast, when applying pseudo position updates, GPS updates seem to have a noticeable effect on the estimated trajectory for the first 70 m only. After that, the estimated trajectory quickly diverges from the true trajectory.

In the case when GPS measurements are not exploited, the trajectory estimated by SC SLU is closest to the true trajectory but PDR also yields an acceptable estimate while PP SLU performs worst when compared to the GPS measurements.

Fig. 7: Performance of PP SLU and PDR on a mixed outdoor and indoor dataset with and without GPS aiding. Results obtained with SC SLU on the same dataset are shown in Fig. 6.

REAL DATA EXPERIMENT: MONOCULAR SLAM INTEGRATION

Fig. 8 demonstrates the applicability of the proposed SC SLU in the context of vision based SLAM. Here, the SC SLU was integrated in the monocular SLAM system that was previously presented by the authors in [8]. It is a well-known fact, that monocular image sequences allow the reconstruction of the trajectory and landmark positions only up to a scale factor. Since the MEMS-IMU employed in this work are in our experience not sufficient to determine this scale factor reliably, it was decided to employ the step length updates to support the scale estimation. For the evaluation presented here, the initialization of new features by the SLAM algorithm was postponed until the 35th step, thereby allowing the filter to assume reliable bias and velocity estimates.

A comparison with the GPS trajectory shows that the overall scale is well met. However, as in the previously described experiment, the GPS signal was in parts disturbed in particular nearby the large office building to the left. This explains the fringes and loops which are present in the GPS trajectory plot.

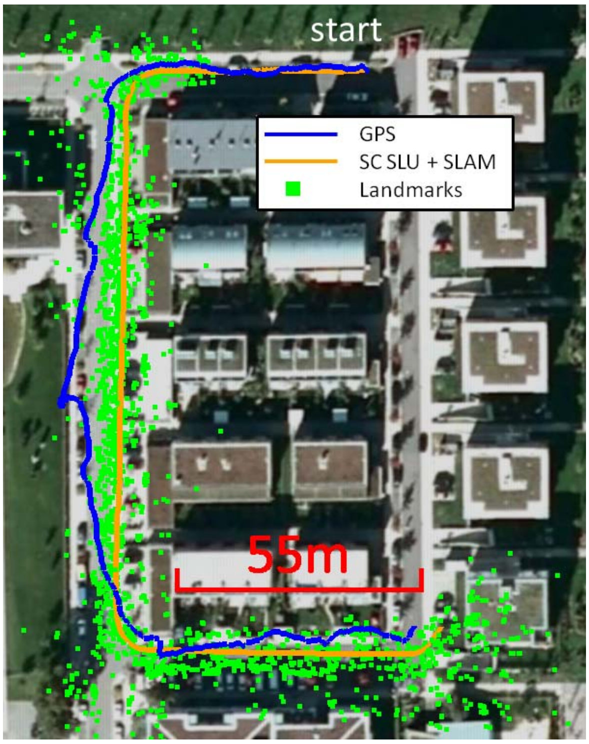

Fig. 8: Result of the integration of the proposed SC SLU in a monocular SLAM system.

CONCLUSIONS AND FUTURE WORK

In this paper a method to process relative position measurements arising from a step detection algorithm within a Kalman filter was presented that builds on the stochastic cloning technique. Experiments with simulated as well real trajectories indicate that this approach is superior to pseudo position measurements. Its main advantage is a correct treatment of the uncertainties arising from the displacement measurements, therefore enabling the combination of step length updates with exteroceptive sensors in a SLAM system or with GPS. First results demonstrating the combination with a monocular SLAM system were presented. In this case the step updates provide a way to determine the scale which is not observable from a monocular image sequence alone. Future work will concentrate on improving the integration in the monocular SLAM system.

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