Multi-Sensor Fusion for Localization of a Mobile Robot in Outdoor Environments

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Abstract

An essential key capability for a mobile robot to perform autonomous navigation is the ability to localize itself in its environment. The most basic way to perform localization is dead-reckoning, i.e., to use relative measuring sensors of the robot like odometry (wheel encoders) by incrementally incorporating the measured revolutions of the robots wheels from a known starting position. As these sensors only deliver relative measurements and all sensors are subjected to noise, the uncertainty of the pose grows boundlessly over the covered distance. In outdoor environments navigation sensors like GPS and compass are a viable option. They are measuring absolute quantities and therefore are not suffering from error accumulation but are prone to local disturbances by surrounding objects. The measurements of the compass are degraded by disturbances of the terrestrial magnetic field, e.g., by metal fences or ventilation fans of air condition systems. Using a low-cost differential GPS receiver, the significant remaining source of error is multipath propagation due to reflections and shadowing effects of large objects like buildings. As the reflections are dependent on the constellation of the receiver and the satellites relative to nearby reflecting surfaces the errors are time variant and locally varying. For precise self localization the combination of several sensors is essential as due to the noisy measurements no single sensor is sufficient. The data from the sensors is fused to a combined estimate resulting in a more accurate localization.

A new Kalman filter based approach will be presented to perform multi-sensor fusion for on-line localization under real-time constraints. While for indoor applications of mobile robots a 2D localization usually is sufficient, as the robot typically operates on flat floors, a full 6 DoF estimation of position and attitude is necessary in outdoor environments where the assumption of a flat ground cannot be applied. To accomplish the 6 DoF estimation relative measuring sensors and absolute measuring sensors are combined by means of multi-sensor fusion. The fusion combines the advantages of the relative measuring sensors regarding their local precision with the capability of absolute sensors to confine the global uncertainty and thus preventing unbounded error growth.

1 Introduction

The AMROS (Autonomous Multisensoric Robots for Security Applications) system, currently developed at Fraunhofer Institute of Optronics, System Technologies and Image Exploitation (IOSB), is an autonomous mobile robotic system for multi sensor outdoor surveillance of real estates and building complexes [1,2]. For safety and security surveillance of endangered public and industrial objects (e.g. stadiums, waterworks, power plants, chemical facilities, etc.) autonomous outdoor inspection robots with the ability to automatically patrol and perform adequate protection operations around the clock can be an efficient and reliable alternative for human guards. Additionally the robots operate in hazardous and dangerous environments without problems. Compared to fixed CCTV installations, which need a great number of cameras in varying and angled spaces, a system with mobile robots as sensor carrier is able to efficiently cover these areas.

1.1 Sensor equipment

To perform autonomous surveillance and security inspection the robot must be able to patrol around a building or navigate to certain points of interest. An essential key capability for the mobile robot to be able to navigate autonomously is to determine where it is located. To localize itself in the environment the mobile robot platform is equipped with several sensors (Figure 1).

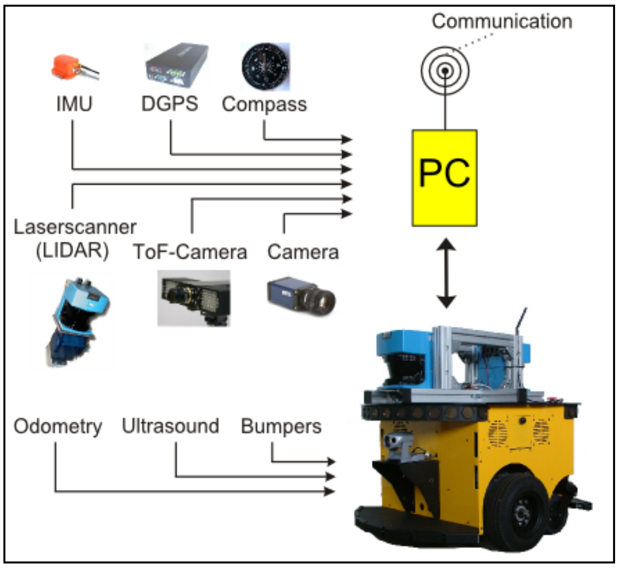

Figure 1 Sensor equipment of the mobile robot.

The sensors can be divided into two categories as follows.

1.1.1 Localization Sensors

Navigation sensors are solely used to determine the pose, i.e., the position and attitude of the mobile robot. These include wheel encoders, which measure the revolutions of the wheels. The robot is also equipped with a low-cost differential GPS receiver based on C/A-Code measurements. It additionally obtains EPS correction data from the SAPOS® service provided by the German State Survey. The data is broadcasted in Germany by UKW radio stations in the RDS carrier, the so called RASANT system [3]. A receiver based on C/A-Code has an accuracy of below 10m GPS without correction data and below 3m with EPS correction data. For the attitude of the robot an inertial measurement unit (IMU) consisting of 3D axial accelerometers, 3D magnetometers and 3D gyroscopes is used in conjunction with an additional digital compass.

1.1.2 Exteroceptive Sensors

Exteroceptive sensors are capable of observing the environment of the mobile robot.

1.1.2.1 Sensors for environment modelling

A laser scanner (LIDAR), stereo cameras and a time-of-flight (ToF) camera are installed on the robot and can be used to build a map of the environment and for surveillance and inspection tasks. Due to the errors in the sensors' measurements the algorithms to build the map have to take the errors and their dependencies into account, which is well-known as the simultaneous localization and mapping problem [5]. The built map can also be used for localization, which has been separately done in [6].
For navigation, a map is advantageous as well because it provides the possibility of path planning beyond the actual sensor coverage. Local path planning includes the map as well as current measurements from the LIDAR and the ToF-camera to avoid dynamic obstacles.

1.1.2.2 Safety Sensors

For safety reasons the robot is equipped with additional ultrasound sensors for collision avoidance if the local path planning based on laser scanner and ToF-Camera failed to discover an obstacle. The ultrasound sensors could also be used for mapping and localization but lead to very inaccurate results because of their wide beam-width and reflections from surfaces.
If all aforementioned sensors fail to detect obstacles and the robot touches an object the bumper buttons are engaged triggering an immediate emergency halt to prevent damage of the robot as well as of the obstacle.

2 Localization and Sensor Fusion

The easiest way to perform localization is dead-reckoning, i.e., to use the odometry sensors (wheel encoders) of the robot by incrementally incorporating the measured revolutions of the robot's wheels from a known starting position. As these encoders only deliver relative measurements and all sensors are subjected to errors, the uncertainty of the pose grows boundlessly over the covered distance. In outdoor environments additional navigation sensors like GPS and compass can be used. They are measuring absolute quantities and therefore are not suffering from error accumulation but are prone to be disturbed locally by surrounding objects.
For precise self localization the combination of several sensors is essential as due to the noisy measurements no single sensor is sufficient. The data from the sensors is fused to a combined estimate resulting in a more accurate localization.

2.1 Error Sources

The odometry is bound to systematic errors depending on the exact determination of the wheel diameter, which can be minimized by calibration. The odometry is still degraded by a statistical error plus sporadic errors from wheel slippage, which occurs mostly while turning.
The compass and the magnetometers of the IMU are disturbed by local interferences of the terrestrial magnetic field for example by metal fences or ventilation fans from air condition systems.
The position estimate of a GPS receiver is influenced by several error sources like varying ionospheric and tropospheric delay, ephemeris and clock errors and multipath propagation [4]. Ground based differential GPS receivers as the one installed on the mobile robot can mitigate all but the latter errors by incorporating correction information from a network of reference stations with known geographic position (Ground Based Augmentation System, GBAS). Based on the actual delay of the received satellite signals the reference stations calculate correction data which is then broadcasted for example by radio stations. While the errors due to ionospheric and tropospheric delay, ephemeris and clock errors can be corrected by differential correction information, the multipath propagation is a local phenomenon depending heavily on the surrounding struc-

tures and cannot be corrected. Errors due to multipath propagation can be up to 10 meters [4].

2.2 Coordinate Transformations

For navigation applications, a number of references for coordinate systems also called frames in three dimensions exist, differing in the origin and three principal axes. In a complex application such as sensor fusion, it is often needed to convert between different frames, as well as to specify one frame as the main one, in which the output is generated [11].
GPS sensors provide the position with latitude, longitude, and altitude values, also referred to as LLA-frame. To combine this position with distances and angles from other sensors, these values can be projected to a plane.

2.2.1 Coordinate Frames

2.2.1.1 $\boldsymbol{b}$-frame

The body-fixed frame has its origin at the rotation center of the moving object. The x-axis is taken as the principal moving direction (forward), the y-axis for sideward movement (right), and the z axis points down, to the direction of the center of the earth if the vehicle is standing upright on the earth's surface. This frame is indicated with superscript *b*.

2.2.1.2 $\boldsymbol{n}$-frame

The navigation frame has the same origin as the b-frame, but the coordinate axes x, y, z point to geographical north, east and down (to the center of the earth), respectively. It is also called the NED-system, short for the employed directions. This frame, as opposed to the other frames, does not use three principal axes in the three-dimensional space, but a projection system to convert from the earth surface to a plane and uses its coordinates instead. This is useful because the earth's curvature is negligible for small distances. This frame is indicated with superscript *n*.

2.2.1.3 $\boldsymbol{i}$-frame

The inertial frame has the origin at the center of the earth. The coordinate axes are defined with respect to fixed celestial objects, which are for many purposes assumed to be inertial, and the z-axis is defined to be the axis around which the earth revolves, pointing to north. This frame is indicated with superscript *i*.

2.2.2 UTM Projection

The process of mapping the points from the surface of the earth to a planar map is called a projection. The earth's surface is a nondevelopable surface, i.e., a surface which cannot be unrolled into a plane without tearing or stretching [7]. Several systems of projection exist and they differ in which attributes they preserve. The Universal Transverse Mercator Projection (UTM) was chosen because it preserves attributes like conformity, which are essential for sensor fusion purposes. The UTM divides the earth surface into regions called UTM zones, and does a Mercator projection separately for each zone. The UTM projection minimizes distortion inside a zone and is conformal, i.e., angels are maintained, which is important for the incorporation of digital compass data. One drawback is that non-uniformities are introduced when changing zones. The latter is negligible for our purposes, as the zones are usually 6° wide and 8° high, which is many orders of magnitude more than the distance that can be covered by the robot on a single charge of battery. Even if it does cross a zone boundary, only a greater momentary error of heading value should be observed.

2.3 Fusion Algorithm

The used sensors are not synchronized and the senor's data rates are different. The naive approach to use the rate of the slowest sensor as the estimation rate of the fusion algorithm is not ideal as a lot of information is discarded and the output rate would be restricted. Therefore the proposed fusion algorithm is capable of incorporating all sensor data with their corresponding incoming rate and thus ensuring the highest possible output rate. Therefore the proposed fusion algorithm is capable of incorporating all sensor data with their corresponding incoming rate and thus ensuring the highest possible output rate.
In addition the fusion algorithm is implemented as an asynchronous cascaded Kalman filter structure to ensure low computational complexity and real-time requirements. The Kalman filter is an optimal estimator for the state of a linear system with a known model from measurements with additive white Gaussian noise [8]. The nine sensors of the inertial measurement unit (IMU) are pre-processed and fused in a separate Kalman filter to estimate the attitude [9]. Cascading of Kalman filters reduces computational complexity and in case of our mobile robot the assumptions regarding independency between position and attitude subsystems are met because of its comparably low dynamics and restricted pitch and roll movements. The estimated attitude is combined with the sensor data of odometry, compass, and GPS in the main Kalman filter resulting in an estimate of the full 6 DoF. Additional meta knowledge about the GPS' error characteristics is incorporated by pre- and post-processing combined with an adaptive tuning of the Kalman filter (Figure 2). The algorithm and used models are explained in more detail in [10].

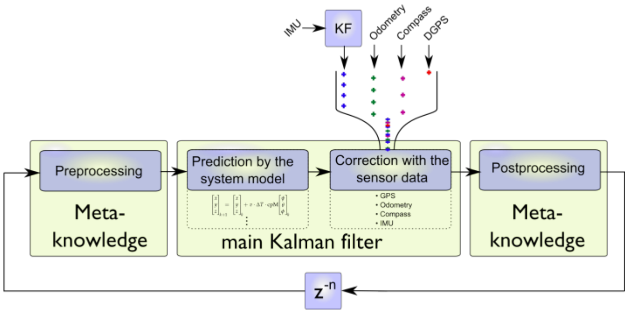

Figure 2 Structure of the fusion algorithm.

2.3.1 Initialization

For the initialization of the position and speed state, it is assumed that the program is invoked while the robot is standing still. The speed is therefore initialized to zero. The absolute position is initially unknown, therefore processing of the inputs from relative sensors like odometry are deferred until a valid position data from an absolute sensor, i.e., GPS and compass, is received which is then used to initialize the position.

The initialization of the attitude is estimated by the cascaded filter for the IMU from the first 50 values.

2.3.2 Meta Knowledge

This includes the knowledge that the position data of the GPS is very unreliable directly after an outage. In this case the error model for the GPS in the Kalman filter is adapted accordingly for a certain period of time after an outage.

Another measure that has been taken into account is the detection of whether the robot is standing still or moving, which can be reliably done with the odometry, and treating the incoming GPS values accordingly.

Because of the very slow convergence when under influence of the multipath propagation, leading to occasional near zero displacements in the GPS position, a displacement threshold Δs_{min} depending on the estimated speed of the mobile robot has been introduced. The corresponding GPS measurements are discarded.

2.3.3 Asynchronous Processing

The GPS receiver has an update rate of 1Hz, the odometry of 10Hz and the compass of 6Hz. The IMU and its Kalman filter are capable of an update rate up to 100Hz. The sensors all have different data rates and also are not synchronized. Not being synchronized would lead to small time offsets when fusing the sensors at the rate of the GPS and a lot of measurements of the other sensor would be omitted. What is more, the system would be limited to the rate of the GPS and susceptible to outages of the GPS, leading to unavailability of estimates for the time of the outages. Thus an asynchronous fusion method was chosen: for every incoming sensor data a prediction and correction step is performed in the Kalman filter, the correction step being done based on the current sensor data only.

2.3.4 System Model

To model system inertia resulting from the limited ability of acceleration and speed limits, a seventh state is added: the scalar speed in the principal direction $v = v_x^n$. This results in the following state vector:

$$x = \begin{bmatrix} x \\ y \\ z \\ v \\ \phi \\ \theta \\ \varphi \end{bmatrix}.$$

The coordinates x, y, z are tracked in the n-frame and, in case of b-frame sensors like odometry, converted from b-frame measurements via the current estimated attitude denoted as a rotation matrix C_b^n:

$$\begin{bmatrix} \Delta x^n \\ \Delta y^n \\ \Delta z^n \end{bmatrix} = C_b^n \begin{bmatrix} \Delta x^b \\ \Delta y^b \\ \Delta z^b \end{bmatrix}.$$

2.3.5 Position Model

The position is predicted according to the current scalar speed v and the time $\Delta T(k)$ between the last two measurements:

$$\begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \\ \hat{v} \end{bmatrix}_{k|k-1} = \begin{bmatrix} 1 & 0 & 0 & \Delta T(k)\cos\hat{\theta}\cos\hat{\phi} \\ 0 & 1 & 0 & \Delta T(k)\cos\hat{\theta}\sin\hat{\phi} \\ 0 & 0 & 1 & -\Delta T(k)\sin\hat{\theta} \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \\ \hat{v} \end{bmatrix}_{k-1|k-1}.$$

The index k does not denote a time index but merely the number of measurements.

2.3.6 Heading Model

The heading angle is treated as a separate system. The odometry only supplies a heading value in b-frame, and the change of this heading value is used as a basis for the change in the heading state in the n-frame. This usage is justified, because the change in the heading value is independent of the other attitude values because of the used convention.

From the odometry data, only the change between two values is calculated and then used for the correction:

$$\varphi_{meas,Odo}(k) = \hat{\varphi}(m|m) + [\varphi_{Odo}(k) - \varphi_{Odo}(m)],$$

where m stands for the last discrete time at which an odometry event has been received. The IMU values are, after they have been processed in their seperate Kalman filter, used in the same way:

$$\varphi_{meas,IMU}(k) = \hat{\varphi}(m|m) + [\varphi_{IMU}(k) - \varphi_{IMU}(m)].$$

The GPS contributes to the heading with an extremely low weighting. The used method only uses the last two GPS values to determine the heading according to the GPS by using the orientation of the vector constructed from the last two GPS points, and the data rate of the GPS is 1Hz whereas the mobility of the robot is much higher:

$$\varphi_{meas,GPS}(k) = \mathrm{atan2}[x_{GPS}(k) - x_{GPS}(k-1); y_{GPS}(k) - y_{GPS}(k-1)].$$

The compass value is used verbatim:

$$\varphi_{meas,Compass}(k) = \varphi_{Compass}(k).$$

2.3.7 Pitch and Roll Model

Both of the pitch and roll values come from a single source, the IMU. As no extra information is available about the error except that the dynamics of a ground vehicle is very low with respect to pitch and roll but suffers from high frequency disturbances because of the roughness of the driving ground, a moving average filter is selected for smoothing.

2.3.8 Speed Model

For the speed, only the odometry and GPS sensors are fused. From the odometry data, the momentary speed is calculated with the last displacement and last time interval:

$$v_{meas,Odo} = \frac{1}{\Delta T(k)} \cdot \sqrt{\left(x_{Odo}(k) - x_{Odo}(k-1)\right)^2 + \left(y_{Odo}(k) - y_{Odo}(k-1)\right)^2}.$$

The GPS data is calculated the same way:

$$v_{meas,GPS} = \frac{1}{\Delta T(k)} \cdot \sqrt{\left(x_{GPS}(k) - x_{GPS}(k-1)\right)^2 + \left(y_{GPS}(k) - y_{GPS}(k-1)\right)^2}.$$

3 Results

A critical problem with the experimentation step is that no reference, so called ground truth, to compare the filtered localization information to, is available. This limitation unfortunately cannot be overcome without using costly sensors like RTK-GPS which could not be obtained.

3.1 Loop Closure

An objective criterion for assessing the performance of the sensor fusion is the error of loop closure, i.e., the distance between the first and last points after returning to a known starting position.

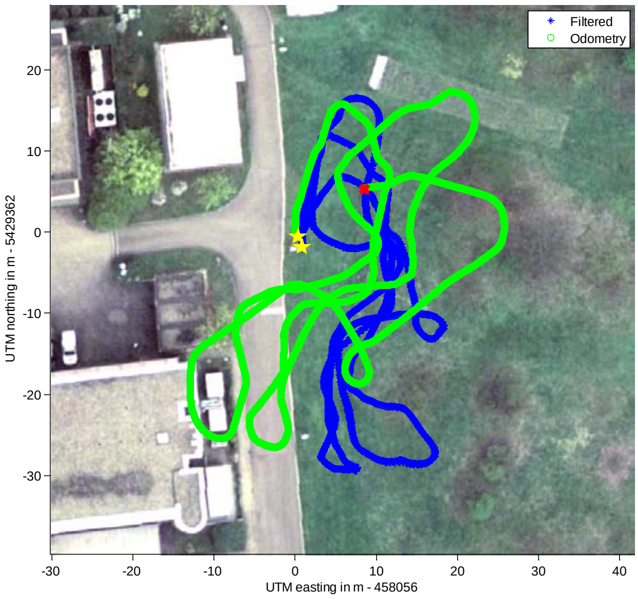

Figure 3 Loop closure

The result is shown in Figure 3. The odometry path is shown in blue and its final position is marked with a red cross. The common starting position and the final position of the filtered path are marked with a yellow star and the filtered path is shown in green. For comparison the start position and heading of the odometry was adjusted according to the first filtered pose.

It can be clearly seen that the filter improves the loop closing quite well. The distance error with odometry only is about 10m, which could be reduced to below 1m.

3.2 GPS outage

Figure 4 shows a situation where several short GPS outages occurred and the results of the compensation capabilities of the fusion algorithm.

Figure 4 GPS outages.

3.3 Oscillation suppression

Due to multipath propagation the GPS position tends to oscillate around the travelled path. Figure 5 shows that the fusion algorithm is capable of suppressing these oscillations effectively.

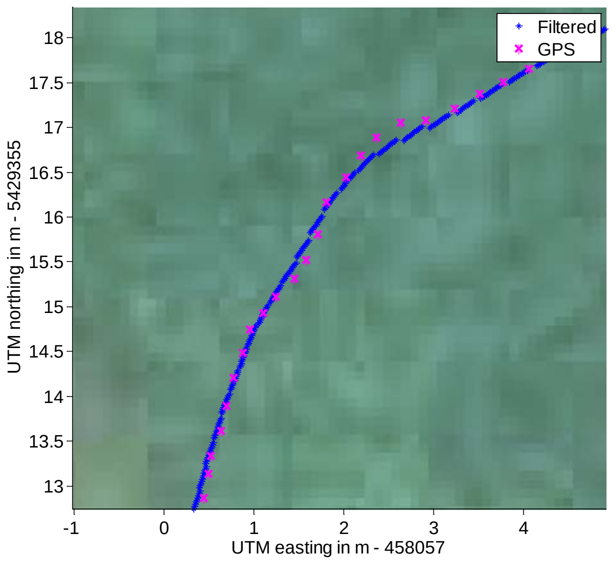

Figure 5 Oscillation suppression

3.4 Sawtooth

A drawback of the asynchronous processing is the occurrence of sawtooth patterns as shown in Figure 6. The relative sensors have higher data rates, and because of the asynchronous fusion technique, for every sensor data a prediction and correction step is performed. Thus, the relative sensor data may cause the position estimate to drift somewhat because of the cumulative errors caused by the addition of the relative measurements. The measurements of the absolute sensors arrive less frequently and correct the position, possibly causing the recently filtered position to be slightly away from the previously estimated pose, which causes small skips in the filtered sensor data. This cannot be overcome with a causal filter which is needed for on-line processing.

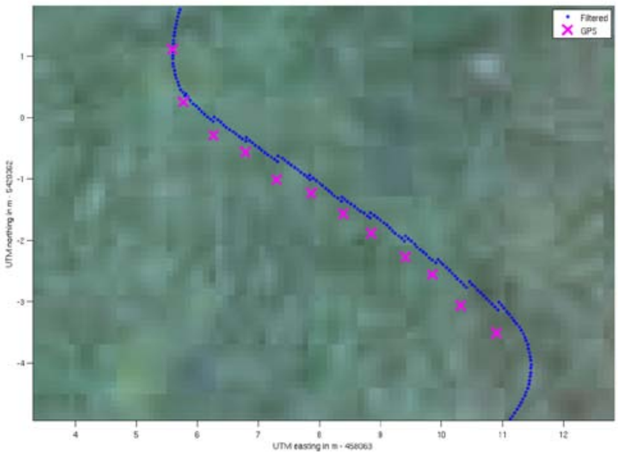

Figure 6 Sawtooth pattern.

4 Conclusion & Outlook

In this paper a new Kalman filter based approach was proposed to perform multi-sensor fusion for on-line localization under real-time constraints for mobile robots. The fusion structure allows for asynchronous processing of sensor data and the cascading of filters reduces the computational cost, which is important for on-line use with constrained computing power. The hybrid concept allows for incorporation of meta knowledge and adaptive tuning of the filter parameters to account for degraded GPS position measurements.

One of the remaining problems is the unavoidable sawtooth pattern, which could algorithmically only be mitigated by acausal smoothing with the present sensor configuration. But this would not comply with real-time constraints for on-line localization of the mobile robot. A GPS receiver with a higher update rate would reduce the sawtooth patterns without the loss of on-line capability. Further improvement can be achieved by using a GPS receiver with raw data output, which allows for a tightly-coupled fusion but also with increased computational cost.

Future work will investigate the combination of the proposed algorithm with SLAM methods and localization in a map respectively [11].

5 Literature

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