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SENSOR FUSION-BASED LOCALIZATION METHODS FOR MOBILE ROBOTS: A CASE STUDY FOR WHEELED ROBOTS

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ABSTRACT

Localization aims to provide the best estimate of the robot pose. It is a crucial algorithm in every robotics application, since its output directly determines the inputs of the robot to be controlled in its configuration space. In real world of engineering, the robot dynamics related measurements are subject to both uncertainties and disturbances. These error sources yield unreliable inferences of the robot state, which inherently result in wrong consensus about the appropriate control strategy to be applied. This outcome may drive the system out of stability and damage both the physical system and its environment. The localization algorithm captures the uncertainties with probabilistic approaches. Namely, the measurement processes are modelled along with their unreliability, moreover, the synergy of multiple information sources is formulated with the aim to calculate the most probable estimate of the robot pose. In essence, this algorithm is composed of two main parts, i.e., first the dynamics of the system is derived, and the corresponding uncertainties are initially predicted, next the additional sensor information is incorporated in the algorithm to refine the posterior estimate. This approach provides the state-of-the-art solution for the derivation of mobile robot poses in real applications.

Keywords: localization, pose estimation, sensor fusion, mobile robot, Kalman filter

1. INTRODUCTION

Mobile robots have a wide application spectrum from industrial applications, over domestic solutions in everyday life, to education platforms at universities [1]. Their popularity is based on the simple mechanical structure, small footprint, easily realizable and agile maneuvers. One of the main purposes of the software architecture, which operates the mobile robot, is the calculation of the suitable control inputs that contribute to successful robot motions. Successful control means that the robot is able to realize the motion between two desired points in its configuration space.

The control structure of mobile robots can be seen in Fig. 1. This control problem is solved in multiple steps. First, the sensors supply measurements of the instantaneous system dynamics. Next, the task of the localization is to obtain the most probable robot pose (position and orientation); i.e., this is a state estimation task. Then, the path planner designs the desired trajectory (series of feasible maneuvers) between the desired points based on both the obtained robot pose and information about its environment (i.e., occupancy grid that characterizes both the free space and obstacles around the robot). Finally, the control algorithm is responsible to track the trajectories, thus it calculates suitable inputs that are supplied to the actuators of the physical system.

In this work, the performance of the extended Kalman filter (EKF) for mobile robot pose estimation is evaluated for two test scenarios based on an experimental setup.

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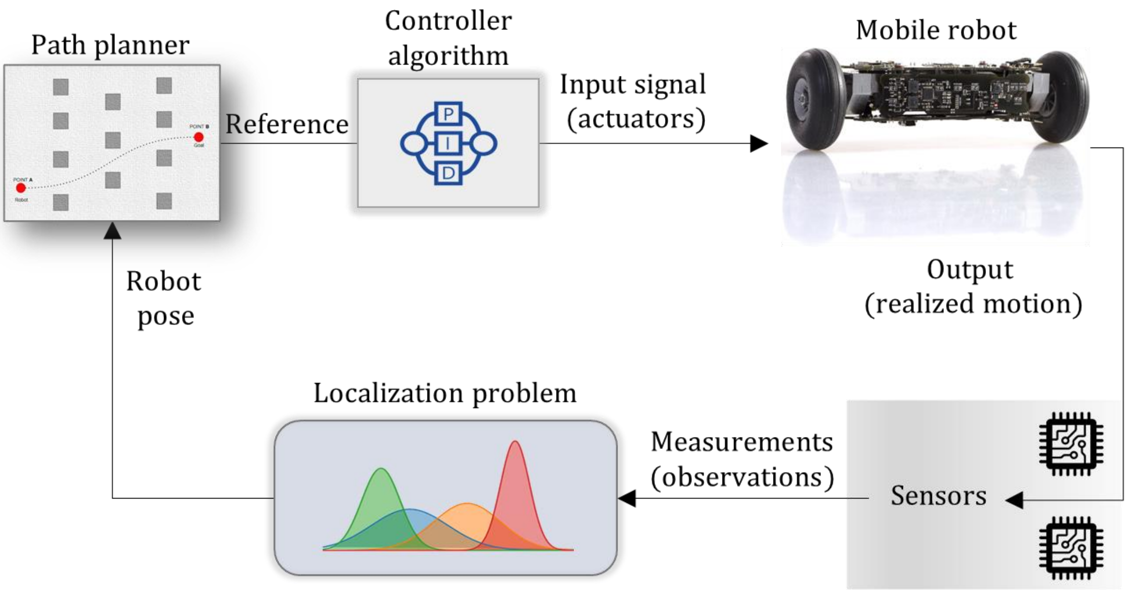

Figure 1: The control structure of mobile robots

2. MATERIALS AND METHODS

The localization problem is solved via fusing multiple independent sensors [2]. It is a recursive algorithm, which first incorporates the uncertainties of each sensor, then formulates the synergy of the applied sensors in a probabilistic framework:

$$p(x_t|map, z_t, u_t) = \eta \cdot p(z_t|x_t, map) \int_C p(x_t|u_t, x_{t-1}) p(x_{t-1}|map, z_{t-1}, u_{t-1})\, dx_{t-1} \quad (1)$$

where η is the normalization factor, C denotes the configuration space of the robot, $p(z_t|x_t, map)$ characterizes the observation, $p(x_t|u_t, x_{t-1})$ describes the motion dynamics, and $p(x_{t-1}|map, z_{t-1}, u_{t-1})$ denotes the probability density function of the system state in the previous epoch.

The problem is addressed in detail in the case of wheeled mobile robots as follows. The relative motion of the system is measured by wheel encoders [3] and/or inertial measurement units (IMU) [3-6]. Wheel encoders measure how many times has the motor rotated, which can be used to calculate distance based on the wheel diameter. IMUs consist of a three-axis accelerometer and a three-axis gyroscope. Accelerometers measure linear acceleration, while gyroscopes provide angular velocity measurements. The orientation can be computed by the integration of the gyroscope signals. By integrating once, the acceleration, the velocity can be given, and the position can be calculated by one further integration.

By the probabilistic characterization of the aforementioned sensors, the motion model of the system is obtained. The motion model describes the system evolution based on the input signals over time. However, the incorporated sensors are imperfect, namely, the inherent noise (e.g., random measurement noise and temperature dependent bias) yields to imprecise motion-model based pose results. On one hand, drift is generated during data processing, on the other hand, the uncertain parameters of the physical system, moreover, the uncertainties induced by the environment of the robot (e.g., uneven, and slippery terrain [3, 7]) significantly reduce the estimation performance and thus the reliability of the so-called a priori estimate.

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The a priori belief $\overline{\mathrm{bel}}(x_t)$ of the robot pose x_t is obtained as follows.

$$\overline{\mathrm{bel}}(x_t) = \int_C p(x_t|u_t, x_{t-1})\mathrm{bel}(x_{t-1})dx_{t-1} \tag{2}$$

The localization algorithm handles the aforementioned problems and compensates for the generated errors in its update phase. The update phase incorporates additional sensors, which provide information of the robot pose in its inertial coordinate system. Namely, the absolute pose data is obtained based on vision sensors, signal strength measurements or global positioning system (GPS). Vision sensors are used in both indoor and outdoor environments, and they include cameras and LiDAR sensors [5-6, 8]. The GPS is a widely used technology for determining absolute position in outdoor environment, but it does not provide reliable measurements in indoor environment [9]. Signal strength measurements are widely used for absolute position estimation in indoor environments [9]. These methods utilize the received signal strength indicator (RSSI), which can be read from the wireless transceiver modules and can be used to estimate distances. The RSSI measurements collected during the communication between the mobile object and so-called anchor nodes, which have known position, can be used to estimate the position of the mobile object. The a posteriori belief $\mathrm{bel}(x_t)$ of the robot pose x_t is given as follows.

$$\mathrm{bel}(x_t) = \eta \cdot p(z_t|x_t)\overline{\mathrm{bel}}(x_t) \tag{3}$$

It should be noted that these measurements are also characterized by anomalies (e.g., noise, low resolution, and low sampling rate). The characterization of these anomalies yields the observation model. In a recursive fashion, the localization algorithm predicts the state of the system with the a priori estimate (via the motion model), while the observation model evaluates this prediction and obtains the refined a posteriori robot pose in a Bayesian estimation framework. This framework is the basis for many popular state-of-the-art algorithms such as the Kalman filter, particle filter, information filter and histogram filter.
In the case of nonlinear systems, the EKF needs to be used, which linearizes about an estimate of the current mean and covariance.

3. RESULTS AND DISCUSSION

3.1. Kalman filter for localization

The Kalman filter is a recursive Bayes filter, which provides the optimal state estimate with minimized error variance [2]. It incorporates linear models for motion $p(x_t|u_t, x_{t-1})$ and observation $p(z_t|x_t, map)$, moreover, it significantly reduces the complexity of estimation by the utilization of normal distributions. The extension of the algorithm enables the usage of nonlinear models, however suboptimal performance is obtained in these cases. Prediction and update phases are given as follows.
Prediction:

$$x_- = f(x_t, u_t) \tag{4}$$
$$P_- = J_F P_t J_F^T + Q \tag{5}$$

Correction:

$$K = P_- J_H^T (J_H P_- J_H^T + R)^{-1} \tag{6}$$
$$x_{t+1} = x_- + K\big(z - h(x_-)\big) \tag{7}$$
$$P_{t+1} = (I - KJ_H)P_- \tag{8}$$

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The algorithm obtains the predicted state along with its covariance (x_- and P_-) based on the system dynamics $f(x_t, u_t)$, Jacobian of the system dynamics (J_F), and covariance matrix of this motion model Q. Then, the Kalman gain is calculated with the help of both the Jacobian J_H of the observation model $h(x_-)$ and covariance matrix of measurement R. This gain determines the importance of instantaneous measurement z and updates the predicted state estimation accordingly.

3.2. Experimental setup

The pose of the mobile robot which performs planar motion is characterized by the position x, y and orientation ϕ. The wheel encoders are used by low level controllers to maintain the instantaneous linear and angular speed values. Thus, the input of the motion model is formulated as:

$$u_t = (v_t, \omega_t)^T. \tag{9}$$

Since the encoders are sensitive to uneven and slippery terrains, therefore it is expected that the input signal-based prediction ensures only short-term accuracy. Complementary measurements are provided by the GPS receiver, which provides observations for the position of the robot:

$$z_t = (x_t, y_t)^T. \tag{10}$$

The motion model is characterized with the state vector x, as given in (11).

$$x = (x, y, \phi, v)^T \tag{11}$$

The motion equations are described in discrete time nonlinear state space. The coordinates of the robot are obtained in the t+1 epoch based on simple discrete time integration as follows.

$$x_{t+1} = x_t + v_t \cos\phi \tag{12}$$
$$y_{t+1} = y_t + v_t \sin\phi \tag{13}$$
$$\phi_{t+1} = \phi_t + \omega_t \, dt \tag{14}$$
$$v_{t+1} = v_t \tag{15}$$

The state estimation performance is influenced by the process and measurement covariance matrices (Q and R). It can be assumed that the state variables are uncorrelated, thus diagonal matrices are defined as in (16) and (17).

$$Q = \mathrm{diag}\left(\sigma_x^2, \sigma_y^2, \sigma_\phi^2, \sigma_v^2\right) \tag{16}$$
$$R = \mathrm{diag}\left(\sigma_{gps,x}^2, \sigma_{gps,y}^2\right) \tag{17}$$

3.3. Simulation results

The performance of the Kalman filter for robot pose estimation based on the described experimental setup is evaluated for two scenarios. The algorithm was implemented in MATLAB/Simulink framework. The robot executed piece wise constant control speeds. The covariance matrices were set up as: $Q = \mathrm{diag}(0.01, 0.01, 0.0003, 1)$ and $R = \mathrm{diag}(1,1)$. The simulations lasted for 60 s and the sampling time was 0.1 s. Fig. 2 and Fig. 3 highlight the simulation results, where the blue line shows the true state of the robot, the red line indicates the state prediction results based on encoder measurements, the yellow dots show the GPS updates, while the purple line indicates the performance of the EKF algorithm, i.e., the state

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estimation results. Tab. 1 and Tab. 2 present the root mean square (RMS) and the standard deviation (STD) of the errors for the two scenarios, which can be calculated using (18) and (19).

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e_i^2} \tag{18}$$

$$\mathrm{STD} = \sqrt{\frac{\sum_{i=1}^{N}(e_i - \bar{e})^2}{N-1}} \tag{19}$$

where N is the number of measurement points, e_i is the error at the ith point, and $\bar{e}$ is the mean error.
It can be seen from the results that the encoder-based state determination does not provide reliable results. This outcome was expected, since the encoder is sensitive to parasitic accelerations, uneven terrain, and slippage, therefore the inevitable noise generates drift during the integration process. However, the EKF successfully combines the short-term accurate encoder results with the GPS updates, thus providing reliable state estimation results for the high-level controllers.

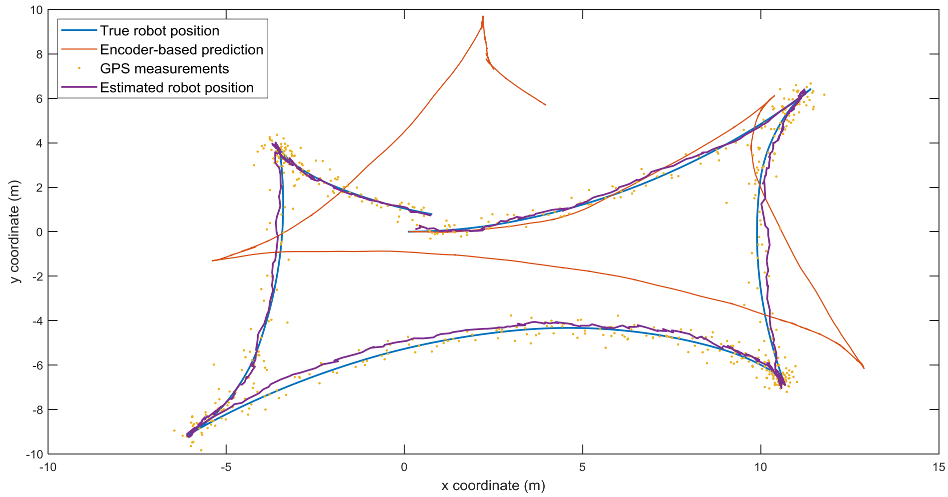

Figure 2: Simulation results in the first scenario

Table 1. Errors (m) in the first scenario

Method	X axis		Y axis	
	RMS	STD	RMS	STD
Encoder	2.7038	2.0510	4.0825	2.7861
EKF	0.1218	0.1218	0.1656	0.1491

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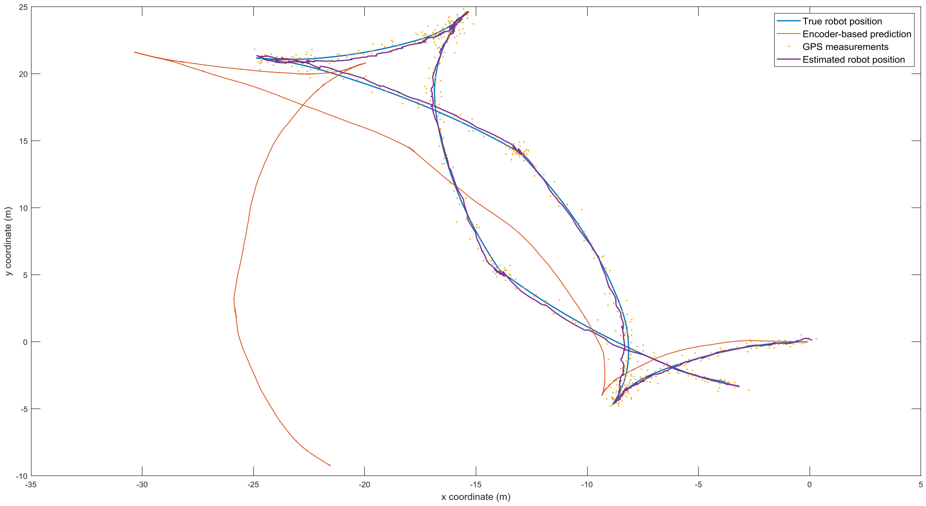

Figure 3: Simulation results in the second scenario

Table 2. Errors (m) in the second scenario

Method	X axis		Y axis	
	RMS	STD	RMS	STD
Encoder	7.2668	4.6859	7.2668	1.9872
EKF	0.1227	0.1226	0.1650	0.1647

4. CONCLUSIONS

The Kalman filter is one of the most popular choices for solving the localization problem of mobile robots. If the system is characterized by uncertainties, then the estimation of robot pose cannot be performed with deterministic approaches. The Kalman filter offers an effective way to address the vagueness of the system; it fuses the information provided by different sources and derives the optimal state estimate with suppressed noise and uncertainty components. Mobile robots operate in environments, where the terrain conditions often change. Variable environment is effectively handled by adaptive strategies, which measure the external disturbance magnitudes and vary the filter parameters during real time operation.

In this paper, the performance of the EKF was evaluated for pose estimation of a mobile robot. Two scenarios were tested based on the experimental setup. The obtained results showed that the encoder-based state determination does not provide reliable results, while the EKF successfully combines the short-term accurate encoder results with the GPS updates and provides reliable state estimation results.

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