Extended Kalman Filter for indoor and outdoor localization of a wheeled mobile robot

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Abstract— **This paper presents a robot localization algorithm, that uses an Extended Kalman Filter (EKF) to fuse data from optical wheel encoders, a gyroscope and an accelerometer for an indoor navigation and additionally from DGPS unit for an outdoor scenario. The algorithm's performance is experimentally evaluated using a skid-steered SeekurJr mobile robot. Experimental results are provided to compare the localization accuracy achieved using the proposed algorithm with those using pure odometry readings and pure DGPS readings.**

I. INTRODUCTION

Localization is an essential task for any mobile robot regardless its application. Various sensors and techniques have been used for robot position estimation that include range sensors (e.g. sonars and laser range finders), video cameras, absolute position sensors (such as GPS and active beacons), inertial sensors and wheel encoders. Setups can vary depending on the mission and navigation environment however the most common minimal sensor setup includes wheel encoders, at least a one axis inertial measurement unit (one-axes accelerometer and one-axis gyroscope) and a GPS unit. In this paper, we will focus on this minimal setup for indoor and outdoor localization.

It is known that measurements from inertial sensors are subject to an unbounded error growth due to integration of the measurement noise and random errors, GPS readings are subject to drop-outs and they are only available outdoor and have a relatively low frequency. Therefore optimal performance can be achieved by measurement fusion using Kalman Filter (KF) techniques [1].

There are a large number of works proposing various KF models for mobile robot position estimation. The authors of [10] propose two indirect KF models, the first one for estimating gyroscope random and deterministic biases with heading estimated from subsequent GPS coordinates and map matching, the second model proposes to use position increments from dead reckoning to construct pseudo range measurements for GPS when the number of visible satellites is less then four. Another work on fusion of wheel encoders and gyroscope data is proposed by [7] where a KF is designed to estimate systematic odometry error and gyroscope bias. The authors of [5] use a KF to estimate robot velocity, rotation rate and 3D orientation by fusion of measurements from wheel encoders, a 3-axis gyroscope and a 3-axis accelerometer. The work of [9] proposes a KF scheme for an indoor navigation that estimates velocities of the left and right wheels of the robot and its rotation rate, using encoder readings and gyroscope data as measurement. For the outdoor navigation they propose using GPS measurements and use a backup position estimates from encoders, a gyroscope and a landmark matching during GPS signal outage. A KF for outdoor navigation using GPS and 6-axis inertial measurement unit is considered in [15]. More examples of the use of a KF for integration of GPS/inertial sensors (INS) can be found in [14], [16], [3], [19]; GPS/odometry in [9], [17], [2]; odometry/INS in [12], [13] to name a few.

Recent works on positioning have been concentrated on adding various sensors to a minimal GPS/INS/odometry set up. Authors of [6] propose a KF to combine odometry with measurements from a compass sensor and an ultrasonic local positioning system. The work of [4] proposes use a ceiling vision system together with odometry measurements

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that are combined together by EKF for indoor navigation. While authors in [11] present a KF to fuse odomentry and INS data with measurements from an omnidirectional vision system. However, these and other examples that are using special sensors go beyond the minimal set up of GPS, INS and odometry that is available for most of the mobile platforms reagrdless of application and thus it is not a focus of this paper.

Most of the work listed above on GPS/INS/odometry integration concentrates either on indoor or outdoor navigation. For the outdoor case, the GPS data is usually taken as the primary position source and INS/odometry is only used during GPS outage. In the indoor case, an indirect KF is often used to estimate errors in odometry and INS measurements, but not the full robot position and orientation.

We propose an EKF scheme for indoor and outdoor scenarios that can easily switch between one another when the measurement model is changing. We estimate the full state of the robot as integrating the position within the filter allows us to compensate for kinematic model inaccuracy which is a part of the process noise. In Section II, we describe the kinematic model of the robot and the Extended Kalman Filter (EKF) algorithm for indoor and outdoor navigation. Section III provides results of experimental trials using the Seekur Jr mobile robot platform, and in Section IV we give a conclusion and a perspective on future work.

II. ROBOT MODEL AND EKF ALGORITHM

A. Kinematic model and state propagation

The robot used in the experiments is a 4-wheel skid-steered platform Seekur Jr manufactured by Adept Mobile robots as shown in figure 1, with two independent motors to drive the left and right side wheels of the robot.

To write the state propagation equations for the Kalman Filter we used a simplified kinematic model known as the unicycle model [8]. Although this model does not perfectly describe the kinematics of the given mobile robot, we aim to compensate for inaccuracy in modelling by running the Kalman Filter. The main benefit of

Fig. 1. Seekur Jr mobile robot platform

in using the unicycle model is that it is applicable for a wide range of mobile robot platforms and thus allows the proposed solution to be easily transferred to a different robot. Robot coordinates in the local navigation frame are shown in figure 2.

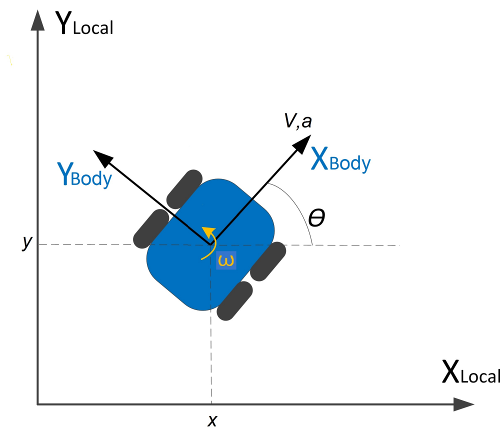

Fig. 2. Robot coordinates in the local navigation frame

We choose the state vector to be $[x, y, \theta, V, \omega, a]^T$ and write the state propagation equations as following:

$$\begin{aligned} x_{k+1} &= x_k + V_k cos(\theta_k)\Delta t \\ y_{k+1} &= y_k + V_k sin(\theta_k)\Delta t \\ \theta_{k+1} &= \theta_k + \omega_k \Delta t \\ V_{k+1} &= V_k + a_k \Delta t \\ \omega_{k+1} &= \omega_k + w_{\omega k} \\ a_{k+1} &= a_k + w_{ak} \end{aligned} \tag{1}$$

where x_k and y_k are the Cartesian coordinates of the robot in the local navigation frame, θ_k is the robot's current heading relative the positive direction of the x-axis of the navigation frame, V_k is the linear velocity of the robot at time t_k, a_k is the linear acceleration at time t_k and ω_k is the angular velocity of the platform about the z-axis at time t_k.

B. Kalman Filter algorithms

The robot is equipped with two optical wheel encoders, an inertial measurement unit and a GPS unit that has a differential GPS (DGPS) service. GPS measurements are only available outdoor and the DGPS service is accessible only on an open field away from buildings. Therefore, we have two measurement models for indoor and outdoor navigation respectively. The indoor measurement vector has four components:

$$z_{indoor} = \begin{bmatrix} V^{od} \\ \omega^{od} \\ \omega^{gyro} \\ a^{accel} \end{bmatrix} \tag{2}$$

where the od superscript stands for $odometry$, $gyro$ for $gyroscope$ and $accel$ for $accelerometer$. Measurements of the translational and the rotational velocities of the robot can be obtained from velocities of the left and right side wheels given by the encoders, where D is the length of the wheel base:

$$V^{od} = \frac{V_L + V_R}{2} \tag{3}$$

$$\omega^{od} = \frac{V_R - V_L}{D} \tag{4}$$

When GPS data is available in the outdoor environment we include GPS position measurements into the measurement vector:

$$z_{outdoor} = \begin{bmatrix} x^{gps} \\ y^{gps} \\ V^{od} \\ \omega^{od} \\ \omega^{gyro} \\ a^{accel} \end{bmatrix} \tag{5}$$

As can be seen from the measurement models, the state vector remains the same for indoor and outdoor navigation, and so do the state transition function and its Jacobian. That makes it very easy to switch between the two EKF models with only changing the measurement vector and resizing the measurement matrix and the covariance matrix of the measurement noise. Figure 3 shows the block-diagram of the algorithm to choose the EKF model.

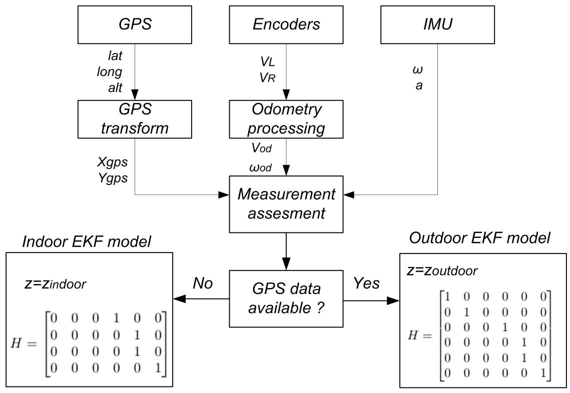

Fig. 3. Block diagram of EKF algorithm

Experimental results for the proposed indoor and outdoor EKF models are provided in Section III.

III. EXPERIMENTS

A. Sensors and software

Robot is equipped with two optical wheel encoders with 10-bit resolution (1024 counts per rotation), ADIS16362 inertial measurement unit (IMU) and a Trimble AG372 GNSS receiver unit with access to a differential GPS service with specified position accuracy 10 cm after convergence. Characteristics of a gyroscope and accelerometers in IMU are given in table I.

Data from wheel encoders and IMU are updated with frequency 10Hz. DGPS unit has a nominal frequency of the measurements 10Hz as well, however exeperiments have shown that there are frequent drop outs when time interval between to subsequent measurements varies from 200msec to 300 msec.

The EKF algorithms we implemented using C++ programming language within the ROS (Robot Operating System) framework. Sensor data acquisition and logging, EKF algorithms and velocity

TABLE I

GYROSCOPE AND ACCELEROMETER SPECIFICATIONS

Gyroscope		
Parameter	**Value**	**Unit**
Initial Bias Error, $\pm 1\sigma$	± 3	$^{\circ}/sec$
Angular Random Walk, 1σ	2	$^{\circ}/\sqrt{hr}$
Output noise	0.8	$^{\circ}/sec\ rms$
Accelerometer		
Parameter	**Value**	**Unit**
Initial Bias Error, $\pm 1\sigma$	6	mg
Velocity Random Walk, 1σ	0.09	$m/sec/\sqrt{hr}$
Output noise	5	$mg\ rms$

control of the robot are all implemented as separate ROS nodes. More information on ROS can be found in [18].
Sensor data logged during experiments is then analysed in Matlab. Matlab was also used for tuning process and measurement noise covariance matrices based on experimental data and then adjusted values were used for covariance matrices in the robot's software.

B. Indoor navigation model

The first experiment is conducted using only measurements from IMU and wheel encoders. For validation purposes the experiment was conducted outdoor which allowed us to have an access to the DGPS measurements,which were used as a reference true trajectory of the robot. We still refer to the experiment as the indoor navigation model test as we used the indoor measurement model (2) for data processing. Below in figure 4 we present the results of the EKF position estimation compared to the true trajectory obtained from the DGPS unit and position estimated from the wheel encoders only. From the figure we can see that the EKF improves estimation of the position on the first 60 meters of run, but after that the estimation accuracy is poor, thus we can make a conclusion that the position estimation using only an IMU and wheel encoders offers limited stability and can not be relay upon for a long distance travelling.

C. Outdoor navigation model

The second experiment provides results obtained using the outdoor EKF model, where

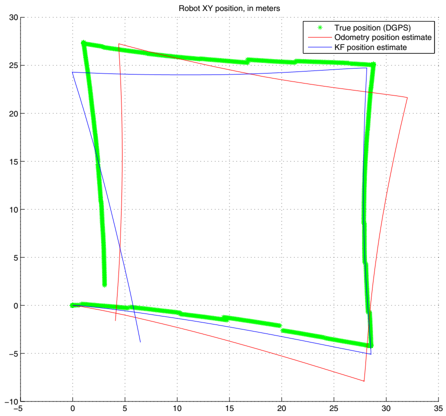

Fig. 4. Experimental results of the EKF position estimation with the indoor measurement model

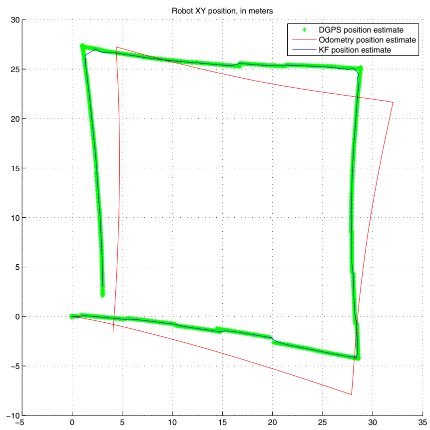

Fig. 5. Experimental results of the EKF position estimation with the outdoor measurement model

IMU and odometry measurements are combined with DGPS position estimates. The outcome of this experiment is shown in figure 5. We can see that the EKF position estimate mostly follows the DGPS position estimate, but gives us a smoother trajectory estimate at the times of DGPS signal interruption.

IV. CONCLUSION AND FUTURE WORK

We have proposed EKF models for indoor and outdoor navigation using IMU, odometry and

DGPS velocity and position estimates. We have conducted experiments to validate the proposed models and showed that the robot localization accuracy is improved compared to that achieved using a single measurement source.

In future work we would like to perform prior calibration of the odometry systematic error that can increase estimation accuracy for the indoor EKF model. Also, we would like to include in the model the roll and the pitch orientation of the robot platform that can be beneficial for the outdoor navigation when travelling on an uneven surface, that affects IMU and odometry measurements. Also, future work will consider the design of a robust version of the proposed filter models that would allow for varying non-systematic odometry error when travelling on a different terrain (e.g. asphalt, sand, wet grass).

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