

2007 9th International Symposium on Signal Processing and its Applications

12-15 February 2007

Sharjah - United Arab Emirates



IEEE



EURASIP



ISSPA

2007

PROCEEDINGS



Start



© 2007 IEEE. Personal use of this material is permitted. However, permission to reprint/republish this material for advertising or promotional purposes or for creating new collective works for resale or redistribution to servers or lists, or to reuse any copyrighted component of this work in other works must be obtained from the IEEE.



ISSPA
2007



2007 9th International
Symposium on Signal Processing
and its Applications
12-15 February 2007
Sharjah - United Arab Emirates

All Papers



Low-Complex Adaptive Post Filter for Enhancement of Coded Video ([Abstract](#))

Andreas Rossholm, Kenneth Andersson, Benny Lövrström



LOWER BOUNDS ON THE PERFORMANCE OF THE MAP EQUALIZER WITH A PRIORI OVER MIMO SYSTEMS ([Abstract](#))

Sihem Chaabouni, Noura Sellami, Aline Roumy



LS-SVM DETECTOR FOR RMSGC DIVERSITY IN SIMO CHANNELS ([Abstract](#))

Omar Abdul-Latif, Jean-Pierre Dubois



Maximum Likelihood Time of Arrival Estimation for UWB Signals ([Abstract](#))

Jaouhar Ayadi, Hai Zhan, John Farserotu



Measure of the Long-Range Persistence of Solar Irradiance Signals Using the Fractal Dimension ([Abstract](#))

Samia Harrouni



MIMO Systems: Performance Comparison of Semi-Blind Techniques ([Abstract](#))

Lamia Berriche, Karim Abed-Meraim, Jean-Claude Belfiore



MOBILE ROBOT EGO-MOTION ESTIMATION BY PROPRIOCEPTIVE SENSOR FUSION ([Abstract](#))

Jose-Luis Blanco, Javier Gonzalez, Juan-Antonio Fernandez-Madrigal

[Back](#)

[Menu](#)

[Next](#)

MOBILE ROBOT EGO-MOTION ESTIMATION BY PROPRIOCEPTIVE SENSOR FUSION

Jose-Luis Blanco, Javier González, Juan-Antonio Fernández-Madrigal
Department of System Engineering and Automation, University of Malaga (Spain)
{jlblanco,jgonzalez,jafma}@ctima.uma.es

ABSTRACT

For any mobile robot it is a major issue that of estimating its position into the working environment. Although this task is partly carried out through external sensors, incrementally computing the ego-motion of the robot using proprioceptive sensors still is a fundamental step to obtain an estimation of the robot displacement. In this work we deal with the sensor fusion problem for the case of a mobile robot equipped with an odometer and an inertial sensor (a gyroscope). We address this problem rigorously through its formulation as a probabilistic estimation problem, developing an efficient solution in the form of an Extended Kalman Filter (EKF), which can be easily implemented in the low-level firmware of a real mobile robot. Experimental results reveal a qualitative improvement in the robot pose estimation for our sensor fusion system when compared with odometry only, which is the most wide spread technique in commercial robots.

1. INTRODUCTION

For mobile robots to become of practical utility in the industry or in the service sector, it is a fundamental prerequisite that they have a certain degree of autonomy. From the set of abilities that this implies for a robot, a remarkable one is to estimate and track its position within the operation environment, namely *localization*. Many practical robot tasks (e.g. navigation, picking and delivering) show up the importance of such ability. Localization is an issue extensively studied in the robotics community, where probabilistic approaches have demonstrated to be the most effective and promising ones [6]. In those approaches a fundamental constituent is the probabilistic, incremental estimation of the robot displacement for close time steps. That is the issue addressed in this work: how to obtain an optimal estimation (under Gaussianity assumption) of the robot displacement from different ego-motion sensors on the robot.

In spite of a number of proprioceptive ego-motion sensors existing for ground mobile robots [2], odometers are included into virtually all commercially available ones. Actually, in most cases odometry is the only ego-motion sensor on the robot. Although other proprioceptive sensors like inertial measurement units

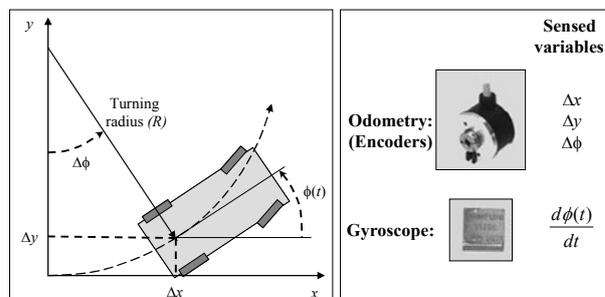


Figure 1. The kinematic model of a planar, differential-driven vehicle is shown at the left. The proprioceptive sensors employed in this work are shown at the right.

(IMUs) may provide valuable information to the displacement estimation, they are not usually integrated into commercial robots. Our aim is to integrate different kinds of ego-motion sensors into a mathematically grounded way, concretely probabilistic Bayesian estimation, while proposing a solution efficient enough (an EKF [4]) to be integrated into the low-level firmware onboard of a real robot. The utility of sensor fusion is revealed by noticing that different sensor weaknesses and advantages may complement to each other: typically, an odometer provides a quite precise estimation of translational movements but performs poorly when the robot turns. In turn, IMUs typically measure rotations more precisely than translations, due to the additional time integration required in the latter.

The rest of this paper is outlined as follows. In section 2 we describe the robot kinematics and the working principles of the considered ego-motion sensors. Next we set up the mathematical formulation involved in sensor fusion, whose implementation in the real system is discussed in section 4. Finally, experimental results are reported in section 5, and we present some conclusions.

2. PROPRIOCEPTIVE SENSORS

In this work we consider a robotic wheelchair [3] equipped with two ego-motion sensors: an odometer, and a gyroscope [1]. We describe next the general kinematic model of this robot and its relation with each of the sensors.

Assuming that the mobile robot moves in a planar environment, its pose is completely defined by its 2D coordinates (x,y) and its heading angle ϕ , as sketched in Figure 1. The kinematic model is the well-known “tricycle model”, where the robot is constrained to move

in circular paths only. Provided that the robot pose is sampled at a high rate (in relation with its speed), it is reasonable to approximate the real robot path by a sequence of short circular arcs. Odometry sensors are composed of two encoders (one on each motor wheel), from whose readings the change in the robot pose $(\Delta x, \Delta y, \Delta \phi)$ can be computed. On the other hand, a gyroscope is a inertial sensor which measures the instantaneous change rate of the robot orientation $\dot{\phi}(t)$, that is the yaw-rate $\frac{d\phi(t)}{dt}$. Please refer to Figure 1 for an illustration of how these variables relate to the robot kinematics.

Since each sensor has its own error sources and they measure different variables from the kinematic model, their combination into a single, optimal estimation is not straightforward. How to perform this is the issue discussed in the next section.

3. SENSOR FUSION

In this work we employ an EKF [4] for fusing the readings from heterogeneous sensors. This filter is an iterative Bayesian filter, where at each instant of time a probability distribution for the system state is kept. An EKF represents probability distributions through multivariate Gaussian distributions, that is, a mean value and a covariance matrix. This distribution is modified according to actuations on the system (prediction step) and next it is corrected according to the sensors measurements (update step). Probabilistic models are required for both the evolution of the system and for the sensors. In the following we present the complete design of an EKF filter for the problem of tracking the pose of a mobile robot equipped with proprioceptive ego-motion sensors only. We will take odometry readings as the action of the robot, whereas gyroscope is considered a sensor of the system state because it is completely passive.

Let \mathbf{x}_k be the state of our system at the discrete time-step k :

$$\mathbf{x}_k = (x_k \quad y_k \quad \phi_k \quad \phi_{k-1})^T \quad (1)$$

where the memory term ϕ_{k-1} stands for the robot orientation at the last time step. If we define Δt as the filter sampling period, the memory term allows us to approximate the robot angular velocity ω_k as:

$$\omega_k \cong \frac{\phi_k - \phi_{k-1}}{\Delta t} \quad (2)$$

Let the estimation at time step $k-1$ be given by the normal distribution $\mathcal{N}(\hat{\mathbf{x}}_{k-1}, \mathbf{P}_{k-1})$, with $\hat{\mathbf{x}}_{k-1}$ and \mathbf{P}_{k-1} being the mean and the covariance matrix, respectively. Then, the prediction step of the EKF filter reads:

$$\begin{aligned} \hat{\mathbf{x}}_k^- &= f(\hat{\mathbf{x}}_{k-1}, u_k) \\ \mathbf{P}_k^- &= (\nabla_{\mathbf{x}_k} f \quad \nabla_{u_k} f) \begin{pmatrix} \mathbf{P}_{k-1} & 0 \\ 0 & \mathbf{C}_{u_k} \end{pmatrix} \begin{pmatrix} \nabla_{\mathbf{x}_k} f^T \\ \nabla_{u_k} f^T \end{pmatrix} \\ &= \nabla_{\mathbf{x}_k} f \mathbf{P}_{k-1} \nabla_{\mathbf{x}_k} f^T + \nabla_{u_k} f \mathbf{C}_{u_k} \nabla_{u_k} f^T \end{aligned} \quad (3)$$

with $f(\cdot)$ being the transition function of the system, and u_k the action performed at time step k whose covariance matrix is \mathbf{C}_{u_k} . The minus sign used as a superscript in (3) means that the estimation is the prior in the Bayesian filter, that is, sensor observations have not being incorporated into the estimation yet.

Since odometry readings are considered the robot actions, we have $u_k = (\Delta x_k \quad \Delta y_k \quad \Delta \phi_k)^T$, and, according to the robot kinematic model, the transition function becomes:

$$f(\hat{\mathbf{x}}_{k-1}, u_k) = \begin{pmatrix} x_k \\ y_k \\ \phi_k \\ \phi_{k-1} \end{pmatrix} = \begin{pmatrix} x_{k-1} + \Delta x_k \cos \phi_{k-1} - \Delta y_k \sin \phi_{k-1} \\ y_{k-1} + \Delta x_k \sin \phi_{k-1} + \Delta y_k \cos \phi_{k-1} \\ \phi_{k-1} + \Delta \phi_k \\ \phi_{k-1} \end{pmatrix} \quad (4)$$

Since it is straightforward to obtain from (4) the Jacobian matrixes $\nabla_{\mathbf{x}_k} f$ and $\nabla_{u_k} f$ required to evaluate (3), they are omitted here due to space limitation. Next, the update step is performed in the iterative filter:

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k \tilde{y}_k \quad (5)$$

$$\mathbf{P}_k = (\mathbf{I}_4 - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^-$$

where \mathbf{I}_4 is a 4×4 unit matrix, and:

$$\begin{aligned} \tilde{y}_k &= z_k - h(\hat{\mathbf{x}}_k^-) \\ \mathbf{S}_k &= (\nabla_{\mathbf{x}_k} h \quad \nabla_{S_A} h \quad \nabla_{n_k} h) \begin{pmatrix} \mathbf{P}_k^- & 0 & 0 \\ 0 & \sigma_{S_A}^2 & 0 \\ 0 & 0 & \sigma_n^2 \end{pmatrix} \begin{pmatrix} \nabla_{\mathbf{x}_k} h^T \\ \nabla_{S_A} h^T \\ \nabla_{n_k} h^T \end{pmatrix} \end{aligned} \quad (6)$$

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T \mathbf{S}_k^{-1}$$

Basically, this step predicts the expected sensor (gyroscope) outcome through the sensor model $h(\cdot)$, its uncertainty (covariance matrix \mathbf{S}_k), and fuse this information with the prior estimation. The gyroscope sensor model could be defined as:

$$h(\hat{\mathbf{x}}_k) = \hat{\omega}_k = \frac{\hat{\phi}_k - \hat{\phi}_{k-1}}{\Delta t} \quad (7)$$

However, the actual sensor readings are analog voltage values, thus we must consider two uncertainty sources in the gyroscope readings z_k : (i) electrical noise, modelled as additive white Gaussian noise (AWGN) with variance σ_n^2 , and (ii) uncertainty in the actual sensor sensitivity, i.e. the volts to deg/s ratio. To integrate the effects of both error sources into the EKF we rewrite (7) to account for S_A and S_N , the actual (unknown) and nominal sensor sensitivity, respectively, and for the noise n_k :

$$h(\hat{\mathbf{x}}_k) = \left(\frac{\hat{\phi}_k - \hat{\phi}_{k-1}}{\Delta t} S_A + n_k \right) \frac{1}{S_N} \quad (8)$$

According to data available in the manufacturer supplied datasheet for our gyroscope, an ADXRS401 [5], it seems that the sensitivity of the device, taken as the outcome of a random variable for each specimen, approximately follows a Gaussian distribution. Therefore, it makes sense to estimate the covariance matrix \mathbf{S}_k by linearization of the sensor model in (8), as shown in (6). There, the Jacobians of the function $h(\cdot)$ $\nabla_{\mathbf{x}_k} h$, $\nabla_{S_A} h$, and $\nabla_{n_k} h$, describe how uncertainty in the system state \mathbf{x}_k , the sensitivity S_A , and the electrical noise

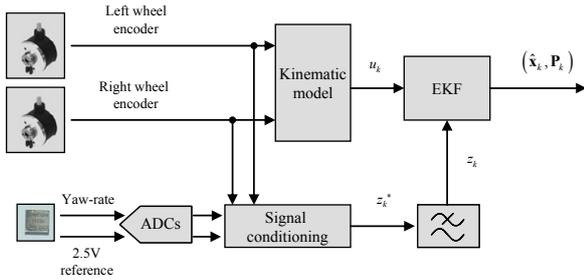


Figure 2. A schematic view of the system implementation.

n_k , correspondingly, are reflected in readings from the gyroscope.

After each iteration of the filter, we obtain the updated *optimal* estimation, disregarding linearization errors.

4. IMPLEMENTATION

Next we discuss how the previously exposed theoretical filter has been integrated into the low-level firmware of a mobile robot.

The system has been designed to work in a timely fashion, under strict real-time requirements. At a working rate of 100Hz, the system collects readings from encoders (odometry) and the gyroscope, performs the required preprocessing of signals, and executes an iteration of the EKF as detailed in section 3. A logical overview of the system is provided in Figure 2. The signal conditioning stage is required since our gyroscope (ADXRS401, see [5]) presents a nonratiometric analog output, while analog-digital converters (ADCs) are ratiometric. Therefore, the resulting readings are highly sensitive to electrical noise coupled to the power supply, which is a major issue on a mobile robot, where motors produce large noise while in operation. To solve this problem, both the sensor output voltage and its 2.5V constant voltage reference are converted through ADCs. The purpose of the signal conditioning stage (please, refer to Figure 2) is two-fold: (i) to scale the sensor readings according to the constant voltage reference; and (ii) to remove the sensor offset, that is, to precisely determinate the voltage corresponding to a null yaw-rate. The offset voltage can be easily estimated by averaging over a time sliding window when the robot is very likely at rest, e.g. when odometry does not detect motion for a few seconds. After removing the offset from the gyroscope signal, it still contains high-frequency electrical noise, which does not carry information about the mechanical system. Since the analog circuitry of the gyroscope has been set up for a measuring bandwidth of 5Hz, we can disregard the signal components at higher frequencies as undesirable noise. In our system the noise is filtered out through a Finite Impulse Response (FIR) implementation of a fourth order elliptic low-pass filter, with a nominal pass-band ripple of 0.1dB, 30dB stopband attenuation, and a cut-off frequency of 5Hz. An example of the signal before and after noise filtering is illustrated in Figure 3.

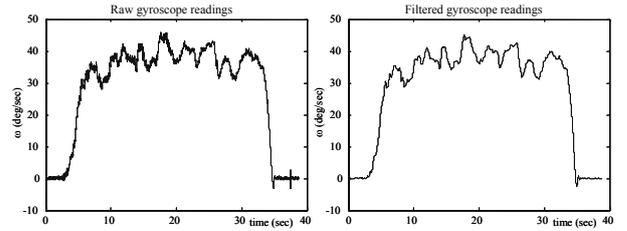


Figure 3. The real signal gathered from the gyroscope, unprocessed (left) and after filtering out the noise (right).

The whole system has been implemented on an ATMEGA128, a low-cost, 8-bit microcontroller from Atmel, which runs at 16MHz. In Figure 4 it is shown the prototype developed in this work, which includes two Micro-Electro-Mechanical Systems (MEMS): the already introduced gyroscope ADXRS401, and a two-axis accelerometer ADXL203, which can be used to detect the gravity vector, i.e. tilt sensing, although such issue is not addressed here. The system runs autonomously and periodically reports the EKF estimation results to a host-PC via a high-speed USB connection. This prototype has been designed with the aim of minimizing costs and weight.

5. RESULTS AND DISCUSSION

Two comparative experiments are reported next, where the robot follows two different paths while its pose is estimated simultaneously from odometry only, and from our sensor fusion system. The actual final robot pose for each trajectory has been determined by a highly-precise laser range scan matching algorithm [1], which we will consider the ground-truth for comparison purposes. The two different paths consist of moving the robot on a twisty forward, and a spinning trajectory, respectively. Results for the first experiment are summarized in Figure 5(a)-(d). It is noticeable the reduction in the final pose uncertainty, both in the robot position and its orientation, for the case of sensor fusion with respect to the odometry estimation only. This is numerically confirmed by the

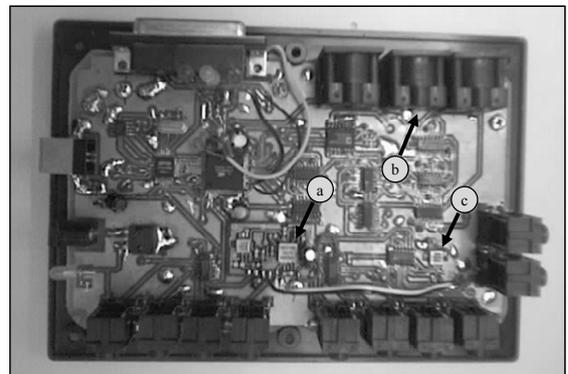


Figure 4. The prototype used in this work as a test bed for sensor fusion. They have been highlighted: (a) the MEMS gyroscope, (b) odometer encoders input, and (c) accelerometers for tilt sensing.

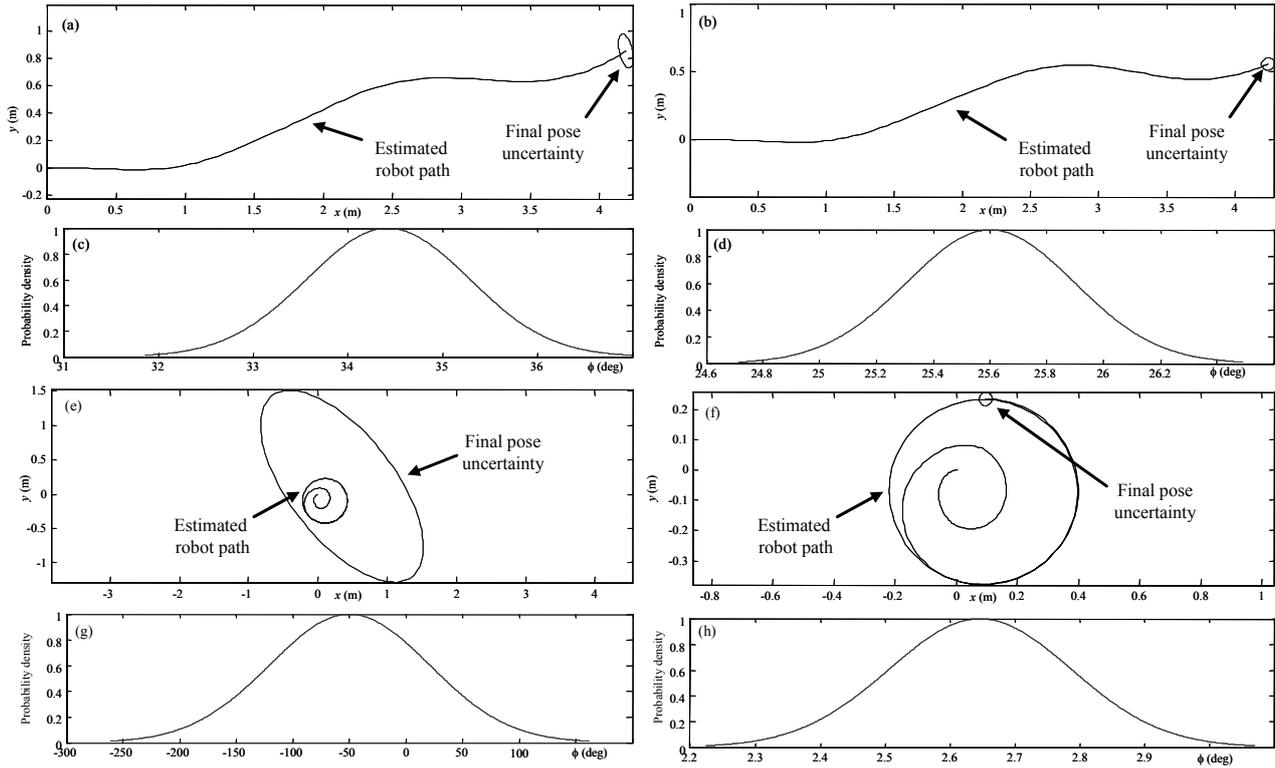


Figure 5. The experimental results from our sensor fusion system. The pair of rows on the top and those on the bottom show, respectively, the results for a twisty forward trajectory and a spinning trajectory. The column on the left represents the estimation from odometry only, while the charts on the right are for the sensor fusion system discussed in this work. It is noteworthy the great reduction in the pose uncertainty, in particular in the spinning trajectory.

values of the covariance matrix determinant: $1.5461 \cdot 10^{-11}$ from odometry only, and $2.0429 \cdot 10^{-13}$ for sensor fusion. In the case of the spinning trajectory, the robot turns three times, which makes the odometry-only estimation to completely lose the robot orientation, as illustrated in Figure 5(e) and (g). The incorporation of yaw-rate information in the estimation provides an impressive qualitative improvement here: the determinant of the covariance matrix, $3.9538 \cdot 10^{-3}$ for the odometry-only estimation, becomes $9.1411 \cdot 10^{-15}$ for the sensor fusion case. As expected, the absolute positioning errors (relative to the ground-truth) are also reduced by the fusion of the two sensors, as summarized in Table I.

	Experiment I: Forward			Experiment II: Spinning		
	x	y	ϕ	x	y	ϕ
Odometry	4.194m	0.849m	34.42°	0.350m	0.114m	-49.55°
Sensor fusion	4.187m	0.934m	25.32°	0.096m	0.233m	2.65°
Ground truth	4.169m	1.031m	25.80°	0.072m	0.282m	2.50°

Table I. Review of experimental results: final estimated pose from each method.

To summarize, in this paper we have presented the problem of proprioceptive sensor fusion for ego-motion estimation for a mobile robot. An efficient solution has been proposed for the case of a robot equipped with odometry and a gyroscope, which has been implemented in the low-level firmware of a real robot and runs in real-

time. Experimental results demonstrate that the sensor fusion system provides a major improvement in the quality of the robot pose estimation.

REFERENCES

- [1] P.J. Besl, N.D. McKay, "A method for registration of 3-D shapes", in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, v.14, no. 2, pp. 239-256, 1992.
- [2] J. Borenstein, H.R. Everett, L. Feng, "Where am I? Sensors and Methods for Mobile Robot Positioning", *University of Michigan*, 1996.
- [3] J. Gonzalez, A.J. Muñoz, C. Galindo, J.A. Fernandez-Madrigal, J.L. Blanco, "A Description of the SENA Robotic Wheelchair", in *the 13th IEEE Mediterranean Electrotechnical Conference (MELECON)*, 2006.
- [4] S.J. Julier, J.K. Uhlmann, "A new extension of the Kalman filter to nonlinear systems", in *Proc. of AeroSense: The 11th Int. Symp. on Aerospace/Defence Sensing, Simulation and Controls*, 1997.
- [5] Online available datasheet for the part ADXRS401, in <http://www.analog.com/>.
- [6] S. Thrun, W. Burgard, D. Fox, "A Probabilistic Approach to Concurrent Mapping and Localization for Mobile Robots", in *Autonomous Robots*, v.5, pp.253-271, 1998.