Multisensor data fusion for differential wheeled mobile robots

[1]*Michal KOPČÍK(1st year),*
Supervisor: [2]Ján JADLOVSKÝ

[1,2]Dept. of Cybernetics and Artificial Intelligence, FEI TU of Košice, Slovak Republic

[1]michal.kopcik@tuke.sk, [2]jan.jadlovsky@tuke.sk

***Abstract*—This paper deals with multisensor data fusion especially for differential wheeled mobile robots using Extended Kalman Filter (EKF). The actual position of the robot can be obtained from several sources. The most basic technique is calculation of the position using odometry which use data from encoders. This approach is very simple and easy to calculate but calculated position tends to drift from real position over time due to slippage between wheels and surface. To reduce this drift there are multiple different sensors placed on the robot. This paper summarizes the knowledge from multiple articles about how to combine data from these sensors using EKF to obtain more precise location of the robot.**

***Keywords*—Mobile robot, localization, Extended Kalman filter, multisensor data fusion.**

I. Introduction

The problematic of multisensor data fusion (MDF) is very actual and it is largely used in systems with enhanced reliability like space probes, vehicles for extraterrestrial planetary exploration, planes, drones, ... Task of MDF is not only to combine data from multiple sensors to enhance precision of the result but also to make system more robust and reliable. To achieve this, sensor fault detection and isolation must be implemented. In our case we want to implement MDF to differential wheeled mobile robot controlled by microcontroller.

The idea is that mobile robot with some defected sensors can be still operational even with some loss of accuracy. To achieve this, mobile robot has to have some redundant sensors to measure the same dimension in some way, like compass and gyroscope.

For MDF there are several approaches. Some of them are mentioned in section II, but this paper is focused to one particular method which is MDF using EKF. The theory about EKF written in this paper is based on several articles such as [1], [2], [3], [4], [5], [6], [7].

Presented algorithm of the EKF will be in the further work tested on differential wheeled mobile robots and tracked mobile robots.

II. Multisensor Data Fusion (MDF)

MDF is the way how to merge data from multiple different sensor to achieve more robust and precise reading of the system state. There are several approaches in MDF such as:

1) Bayes' Rule.
2) Probabilistic Grids.
3) Sequential Monte Carlo Methods.
4) The Kalman Filter.

A. Bayes' Rule

Bayes' rule is the most common method of most data fusion methods. It provides conclusion about state of the system with respect to the observation. Bayes rule requires that the relationship between state of the system and its observation is given as a joint probability or joint probability function for discrete or continuous variables [8].

B. Probabilistic Grids (PG)

PG are generally the simple way how to implement Bayesian data fusion methods and they can be used in mapping and tracking [9].

C. Sequential Monte Carlo Methods

Monte Carlo (MC) filter methods describe probability distributions as a set of weighted samples of an underlying state space. MC filtering then uses these samples to simulate probabilistic inference usually through Bayes' rule. Many samples or simulations are performed. By studying the statistics of these samples as they progress through the inference process, a probabilistic picture of the process being simulated can be built up [8]. More information about mobile robot MC localization can be found [10], [11].

Although the MC method gives relatively precise results, for our purpose this approach is not appropriate because of very high demands on processing power that microcontroller does not provide.

D. The Kalman Filter (KF)

The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state.

Although the Kalman filter was developed in early 60's by Rudolf E. Kálmán, it is still largely used. There are several modifications of basic KF such as:

1) Linear Kalman filter (LKF / KF).
2) Extended Kalman filter (EKF).
3) Constrained Kalman filter (CKF).
4) Unscented Kalman filter (UKF).

5) Hybrid Kalman filter.
6) Kalman-Buncy filter.

Almost all modifications of KF can be used to solve problem of multisensor data fusion and localization. From these types of KF we decided to use EKF because of its good performance and its suitability for estimating nonlinear systems. The demand on processing power for EKF is quite large, but it is significantly lower than using MC algorithms. There are several articles in which authors use for MDF and localization of the robot for example Unscented Kalman filter [12], [13] or Constrained Kalman filter [14], [15].

III. Multisensor data fusion using extended Kalman filter

In this section the MDF using EKF is described. In this case we used only kinematic model for EKF MDF method

A. Kinematic model of the mobile robot

Mobile robot is defined in space by three dimensions namely coordinates x, y and the angle of the robot φ. These three dimensions form state vector of the robot $\mathbf{x}(k)$. The input vector $\mathbf{u}(k)$ consists of the translation motion change Δs and rotation change $\Delta\varphi$. Discrete state vector and input vector of the differential wheeled mobile robot is shown (1).

Alternatively the voltages to the motors can be used as input vector to the kinematic model, but for this, dynamic model of the mobile robot is required. Dynamic model of the robot can be acquired using experimental or analytical identification [16], [17]

$$\mathbf{x}(k) = \begin{bmatrix} x \\ y \\ \varphi \end{bmatrix}(k),\ \mathbf{u}(k) = \begin{bmatrix} \Delta s \\ \Delta\varphi \end{bmatrix}(k) \tag{1}$$

To determine actual position of the mobile robot, it is necessary to know the kinematic model of the mobile robot. EKF requires the system to be given in certain form (2).

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k)) + \mathbf{v}(k) \\ \mathbf{z}(k) &= \mathbf{h}(\mathbf{x}(k)) + \mathbf{w}(k) \end{aligned} \tag{2}$$

Vector $\mathbf{z}$ consists of measured data from all of the sensors such as compass, gyroscope, accelerometer, ... Vectors $\mathbf{v}$ and $\mathbf{w}$ are System and Measurement uncorrelated white noise, whose mean value is $E\{\mathbf{v}(k)\} = E\{\mathbf{w}(k)\} = 0$ For differential wheeled mobile robot with state vector $\mathbf{x}(k+1)$, the kinematic model is given by (3).

$$\mathbf{x}(k+1) = \begin{bmatrix} x(k) + \Delta s(k)\cos(\varphi(k) + \frac{1}{2}\Delta\varphi(k)) \\ y(k) + \Delta s(k)\sin(\varphi(k) + \frac{1}{2}\Delta\varphi(k)) \\ \varphi(k) + \Delta\varphi(k) \end{bmatrix} \tag{3}$$

Mostly as input to the kinematic model are used distances traveled by wheels $\Delta s_R(k)$ and $\Delta s_L(k)$ over the time Δt instead of $\Delta s(k)$ a $\Delta\varphi(k)$. For this conversion the equations (4) can be used, where constant d is distance between wheels.

$$\begin{aligned} \Delta s(k) &= \frac{\Delta s_R(k) + \Delta s_L(k)}{2} \\ \Delta\varphi(k) &= \frac{\Delta s_R(k) - \Delta s_L(k)}{d} \end{aligned} \tag{4}$$

B. Measurement model of the mobile robot

The measurement function (MF) $h_i(\mathbf{x}(k))$ gives the expected measurement of sensor i according to current state [6]. This means, that for each sensor there is one MF that translate state of the robot to measurement of the sensor and vice versa. Equation (5) shows the overall MF, where n is the sum of the sensed dimensions by all sensors.

$$h(\mathbf{x}(k)) = \begin{bmatrix} h_1(\mathbf{x}(k)) \\ h_2(\mathbf{x}(k)) \\ \dots \\ h_n(\mathbf{x}(k)) \end{bmatrix} \tag{5}$$

For example the MF $h_{cz}(\mathbf{x}(k))$ for compass in z axis $z_{cz}(k)$ will be (6).

$$z_{cz}(k) = h_{cz}(\mathbf{x}(k)) = \varphi(k) \tag{6}$$

C. EKF for differential wheeled mobile robot

For many systems, the EKF has proven to be usefull method of obtaining good estimates of the system state. EKF in contrast to basic KF can be used to estimate system state of non-linear system by linearizing it in each discrete time step using Jacobian matrixes of the system that are not constant.

In this article we will use EKF for estimating of the robot's system state and for data fusion from multiple sensors.

EKF takes in count process noise $\mathbf{v}(k)$ and sensors data noise $\mathbf{w}(k)$, which we assume are Gaussian zero mean uncorrelated noise. Elements $\sigma^2_{\Delta\varphi}$ and $\sigma^2_{\Delta s}$ of process noise covariance matrix $\mathbf{Q}$ can be obtained empirically or from measured data of real system. These covariances basically mean how much we trust estimates. Covariance matrix $\mathbf{R}$ is diagonal matrix which individual elements express how we trust given sensors.

$$\mathbf{Q} = \begin{bmatrix} \sigma^2_{\Delta\varphi} & 0 \\ 0 & \sigma^2_{\Delta s} \end{bmatrix} \tag{7}$$

Jacobian matrixes for defined system (2) can be calculated using (8).

$$\nabla\mathbf{f_x} = \left.\frac{\partial\mathbf{f}}{\partial\mathbf{x}}\right|_{\hat{x}_{k|k}},\ \nabla\mathbf{h_x} = \left.\frac{\partial\mathbf{h}}{\partial\mathbf{x}}\right|_{\hat{x}_{k|k}} \tag{8}$$

For differential wheeled robot and for robot with tracks the system jacobian matrix $\nabla\mathbf{f_x}(k)$ is (9).

$$\nabla\mathbf{f_x}(k) = \begin{bmatrix} 1 & 0 & -\Delta s(k)\cos(\varphi(k) + \frac{1}{2}\Delta\varphi(k)) \\ 0 & 1 & \Delta s(k)\sin(\varphi(k) + \frac{1}{2}\Delta\varphi(k)) \\ 0 & 0 & 1 \end{bmatrix} \tag{9}$$

Prediction In first step the EKF predicts position of the robot one step ahead by using equation of the kinematic model of the mobile robot and data from encoders.

The prediction of the system state vector $\hat{\mathbf{x}}(k \mid k-1)$ and its covariance matrix $\mathbf{P}(k \mid k-1)$ at discrete time step k can be calculated using (10).

$$\begin{aligned} \hat{\mathbf{x}}(k \mid k-1) &= \mathbf{f}(\hat{\mathbf{x}}(k-1 \mid k-1), \mathbf{u}(k)) \\ \mathbf{P}(k \mid k-1) &= \nabla\mathbf{f_x}(k)\mathbf{P}(k-1 \mid k-1)\nabla\mathbf{f_x}^T(k) + Q \end{aligned} \tag{10}$$

After this, the innovation covariance matrix $\mathbf{S}(k)$ can be calculated according to (11).

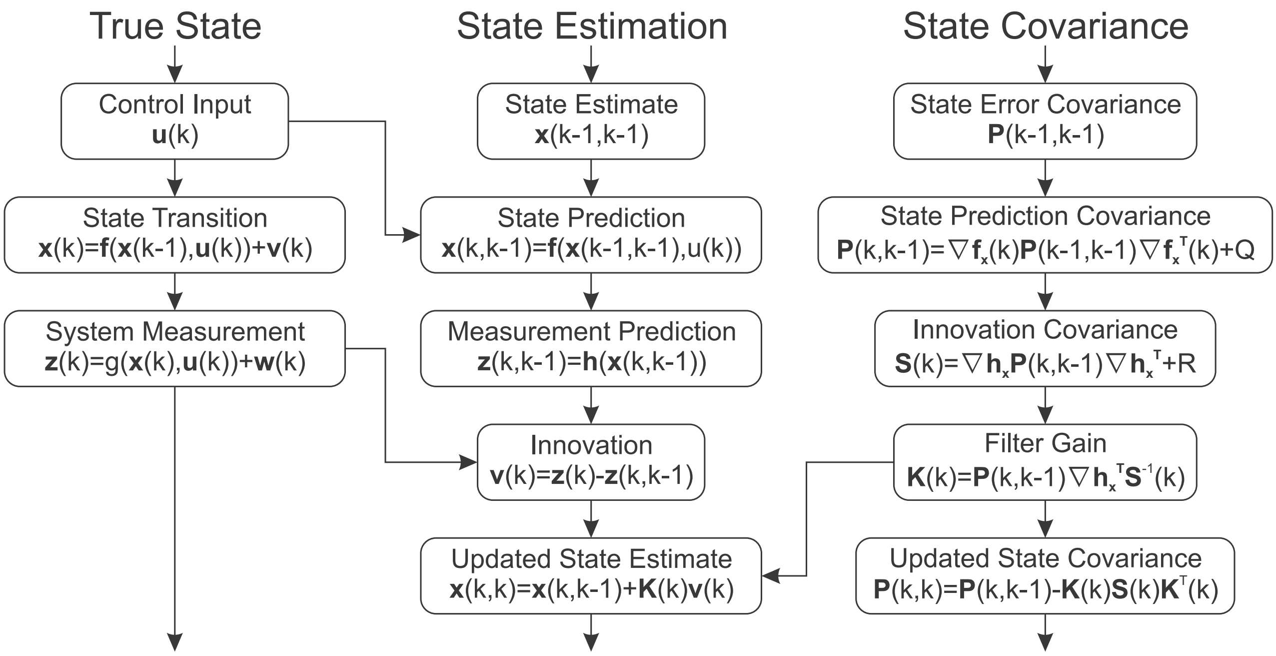

Fig. 1: Block diagram of the Extended Kalman filter cycle [8], [18]

$$\mathbf{S}(k) = \nabla\mathbf{h_x}\mathbf{P}(k \mid k-1)\nabla\mathbf{h_x}^T + R \tag{11}$$

The KF gain matrix $\mathbf{K}(k)$ can than be calculated using (12).

$$\mathbf{K}(k) = \mathbf{P}(k \mid k-1)\nabla\mathbf{h_x}^T\mathbf{S}^{-1}(k) \tag{12}$$

Update

At time k an observation z(k) is made and the updated estimate $\hat{\mathbf{x}}(k \mid k)$ of the state $\mathbf{x}$, together with the updated estimate covariance $\mathbf{P}(k \mid k)$ is computed from the state prediction and observation according to

First, the updated covariance matrix $\mathbf{P}(k \mid k)$ is calculated (13).

$$\mathbf{P}(k \mid k) = \mathbf{P}(k \mid k-1) - \mathbf{K}(k)\mathbf{S}(k)\mathbf{K}^T(k) \tag{13}$$

Then after measurement $\mathbf{z}(k)$ is made, the correction vector $\mathbf{v}(k)$ can be calculated by (14).

$$\mathbf{v}(k) = (\mathbf{z}(k) - \nabla\mathbf{h_x}\hat{\mathbf{x}}(k \mid k-1)) \tag{14}$$

The last step is to calculate the updated state estimate $\hat{\mathbf{x}}$ using (15).

$$\hat{\mathbf{x}}(k \mid k) = \hat{\mathbf{x}}(k \mid k-1) + \mathbf{K}(k)\mathbf{v}(k) \tag{15}$$

Figure 1 shows the overall block diagram of one EKF cycle.

D. EKF testing

The implementation and testing of EKF algorithm on real mobile robot will consist of three main steps:

1) Offline data processing
2) Online remote calculation of the position.
3) Online embedded calculation of the position.

To test the precision of calculated data from EKF MDF, it is necessary to have information about real position and angle of the robot. This information will be obtained from the camera located above the surface on which the robot will move.

Offline data processing First the robot will be used as remote agent to collect data from all of the sensors and transmit them to the computer. After the run the EKF algorithm will be tested offline on collected data and the calculated position will be compared to real position obtained from the camera. *Online remote data processing* In next step the mobile robot will also be used as remote agent, but the EKF algorithm will run online on computer. *Online embedded calculation of the position* In final step, the EKF algorithm will run on microcontroller, with supervision using computer.

IV. Mobile robots

In further work we are planning to test presented EKF algorithm on given mobile robots.

A. Mobile robot for MiroSot competition

This mobile robot is robotic soccer player for MiroSot league. It is controlled by 32-bit ARM microcontroller mounted on custom made PCB. This robot features digital accelerometer and gyroscope, magnetic rotary encoders and bluetooth communication module. Currently new version of this type of robot is under development. The photo of MiroSot soccer player robot is shown on figure 2. More information about this robot can be found [19].

B. Mobile robot ALFRED

ALFRED is mobile robot designed for line following tasks. He is controlled by 8-bit PIC microcontroller. ALFRED features five reflective infrared sensors to detect line, ultrasound distance sensor and bluetooth communication module. The photo of ALFRED is shown on figure 3. More information about this robot can be found [20].

C. Tracked mobile robot TrackBot

TrackBot is tracked mobile robot controlled by Arduino UNO. It features digital compass, gyroscope and accelerometer, six reflective infrared distance sensors, bluetooth communication module and a gripper. Currently mobile robot TrackBot is under development.

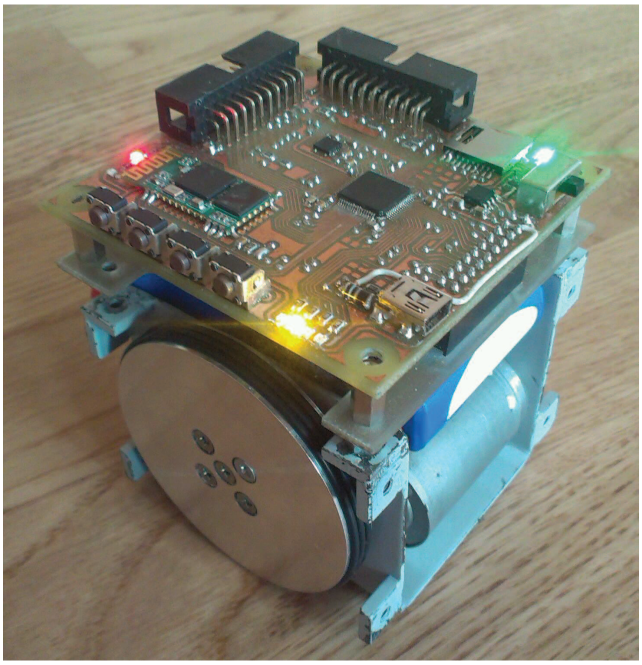

Fig. 2: Photo of mobile robot for MiroSot soccer compettition

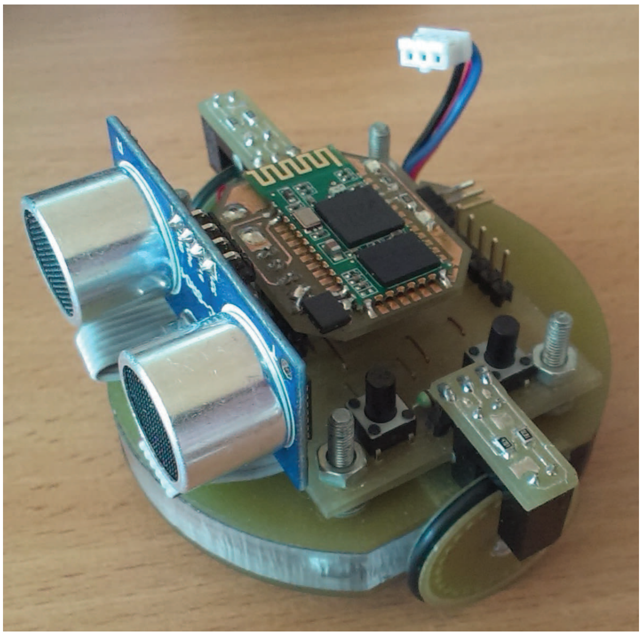

Fig. 3: Photo of mobile robot ALFRED

Acknowledgment

This work has been supported by the Scientific Grant Agency of Slovak Republic under project Vega No.1/0286/11 Dynamic Hybrid Architectures of the Multiagent Network Control Systems (50%) and project KEGA 021TUKE-4/2012 (50%).

References

[1] M. Pinto, A. Moreira, and A. Matos, "Localization of mobile robots using an extended kalman filter in a lego nxt," *Education, IEEE Transactions on*, vol. 55, no. 1, pp. 135–144, Feb 2012.

[2] S. Kwon, K.-W. Yang, and S. Park, "An effective kalman filter localization method for mobile robots," in *Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on*, Oct 2006, pp. 1524–1529.

[3] F. Kong, Y. Chen, J. Xie, G. Zhang, and Z. Zhou, "Mobile robot localization based on extended kalman filter," in *Intelligent Control and Automation, 2006. WCICA 2006. The Sixth World Congress on*, vol. 2, 2006, pp. 9242–9246.

[4] ——, "Mobile robot localization based on extended kalman filter," in *Intelligent Control and Automation, 2006. WCICA 2006. The Sixth World Congress on*, vol. 2, 2006, pp. 9242–9246.

[5] G. Cotugno, L. D'Alfonso, W. Lucia, P. Muraca, and P. Pugliese, "Extended and unscented kalman filters for mobile robot localization and environment reconstruction," in *Control Automation (MED), 2013 21st Mediterranean Conference on*, June 2013, pp. 19–26.

[6] T. J. Otahal and H. G. Tanner, "Extended kalman filter implementation for the khepera ii mobile robot," 2009.

[7] V. Sangale and A. Shendre, "Localization of a mobile autonomous robot using extended kalman filter," in *Advances in Computing and Communications (ICACC), 2013 Third International Conference on*, Aug 2013, pp. 274–277.

[8] B. Siciliano and O. Khatib, *Springer Handbook of Robotics*. Springer, 2008, no. 1. [Online]. Available: http://www.springer.com/978-3-540-23957-4

[9] B. Merhy, P. Payeur, and E. Petriu, "Application of segmented 2d probabilistic occupancy maps for mobile robot sensing and navigation," in *Instrumentation and Measurement Technology Conference, 2006. IMTC 2006. Proceedings of the IEEE*, April 2006, pp. 2342–2347.

[10] Z. Liang, X. Ma, and X. Dai, "Extended monte carlo algorithm to collaborate distributed sensors for mobile robot localization," in *Robotics and Biomimetics, 2007. ROBIO 2007. IEEE International Conference on*, Dec 2007, pp. 1647–1652.

[11] F. Dellaert, D. Fox, W. Burgard, and S. Thrun, "Monte carlo localization for mobile robots," in *Robotics and Automation, 1999. Proceedings. 1999 IEEE International Conference on*, vol. 2, 1999, pp. 1322–1328 vol.2.

[12] M. Anjum, J. Park, W. Hwang, H. il Kwon, J. hyeon Kim, C. Lee, K. soo Kim, and D. il Cho, "Sensor data fusion using unscented kalman filter for accurate localization of mobile robots," in *Control Automation and Systems (ICCAS), 2010 International Conference on*, Oct 2010, pp. 947–952.

[13] N. Houshangi and F. Azizi, "Accurate mobile robot position determination using unscented kalman filter," in *Electrical and Computer Engineering, 2005. Canadian Conference on*, May 2005, pp. 846–851.

[14] H. Myung, H.-K. Lee, K. Choi, S. Bang, Y. Kim, and S. Kim, "Mobile robot localization using a gyroscope and constrained kalman filter," in *SICE-ICASE, 2006. International Joint Conference*, Oct 2006, pp. 2098–2103.

[15] H. Myung, H.-K. Lee, K. Choi, S.-W. Bang, Y.-B. Lee, and S.-R. Kim, "Constrained kalman filter for mobile robot localization with gyroscope," in *Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on*, Oct 2006, pp. 442–447.

[16] E. Mendes and A. A. D. Medeiros, "Identification of quasi-linear dynamic model with dead zone for mobile robot with differential drive," in *Robotics Symposium and Intelligent Robotic Meeting (LARS), 2010 Latin American*, Oct 2010, pp. 132–137.

[17] M. Morales, V. Alexandrov, and J. Arias, "Dynamic model of a mobile robot with two active wheels and the desing an optimal control for stabilization," in *Electronics, Robotics and Automotive Mechanics Conference (CERMA), 2012 IEEE Ninth*, Nov 2012, pp. 219–224.

[18] D. Hugh, "Introduction to sensor data fusion." Australian Centre for Field Robotics The University of Sydney, 2002.

[19] M. Kopcik and R. Bielek, "Construction and operating system of robosoccer agents," in *13th Scientific Conference of Young Researchers : May 14th, 2013, Herlany, Slovakia*, May 2013, pp. 80–84.

[20] M. Kopcik, "Basic motion control of differential wheeled mobile robot ALFRED," symposium on Emergent Technologies in Artificial Intelligence and Robotics, September 2013, Kosice, Slovakia, unpublished.