2014 14th International Conference on Control, Automation and Systems (ICCAS 2014)
Oct. 22-25, 2014 in KINTEX, Gyeonggi-do, Korea

Implementation of Unscented Kalman Filter for Mobile Robot Localization Fusing Ultrasonic Sensor and Laser Range Finder Measurements

Sairah Naveed[1] and Nak Yong Ko[2*] Seokki Jeong[3]

[1,3] Department of Control and Instrumentation Engineering, Chosun University,
Gwangju, 501-759, Korea (sairah.naveed@hotmail.com , seak-ki@hanmail.net)
[2] Department of Control, Instrumentation and Robot Engineering, Chosun University,
Gwangju, 501-759, Korea (nyko@chosun.ac.kr) * Corresponding author

Abstract: This paper reports a method for mobile robot localization in an indoor environment. The work space consists of tables, chairs on the floor and ultrasonic beacons attached on the ceiling of the room. The robot navigates through defined way points on the floor. The robot is fed with distance to wall information from laser range finder, and ranges from beacons from an ultrasonic receiver. The robot collects the proprioceptive information from its wheel encoders. We propose the modified UKF localization algorithm fusing the measurements of ultrasonic sensor, and laser range finder. The additional part of the proposed algorithm also computes correspondence which associates a range data to a beacon. The performance of the proposed algorithm is evaluated by using different sets of control parameter values which describes motion and measurement noise.

Keywords: Data association, laser range finder, unscented Kalman filter, ultrasonic sensor.

1. INTRODUCTION

The robot localization is one of the key issues in making a robot truly autonomous. If a robot does not know where it is, it can be difficult to determine what to do next. For localization robot has to get access to its motion information, sensor measurement data and the situation of an environment around the robot.

Probabilistic approaches are the most promising candidates which provide the real-time solution to the robot localization issues. Kalman filter approach is most popular approach to solve the localization problem. All the Kalman filters use Gaussian distribution for estimation. There are several variants of Kalman filter but the most popular are extended Kalman filter (EKF) and unscented Kalman filter (UKF). EKF employs Jacobian derivation to approximate the non-linearity of the system. However, EKF face considerable hurdles in case of non-Gaussianity, high dimensionality which lack to localize the robot. On the other hand UKF approximates the non-linearity of the system up to more degrees than EKF. It applies the new approximate method called as *unscented transform* [1] which uses the set of samples called as sigma points for state transition. UKF is favorable when the system is highly non-linear and derivation of Jacobian is not feasible.

A variety of localization methods for mobile robots have been researched. Dead reckoning has long being used for localization. This method estimates the robot by using robot motion information over time. Other localization system use beacons placed at known position in the environment [2]. It uses electronic pulses to determine the distance between the robot and beacons, and estimate a position of the robot. Besides the method of localization is a laser range finder [3]. This sensor is used for calculating the range, but its data can be used in many ways. Despite of its high cost it is very precise, reliable and a high speed sensor.

Reliable robot localization is the long awaited requirement for most robotic researchers. One of the requirements of localization is to localize the robot in a partially unknown environment, which makes robot pose estimation difficult. Aiming at this issue we propose the UKF based algorithm fusing ultrasonic sensor and laser range finder measurements. We develop the work space cluttered with tables, chairs, and ultrasonic beacon attached on the ceiling of the room. The most of the geometry of work space is modeled with grid-based map while the ultrasonic beacons considered as landmark. The correspondence of range which associates to each beacon is unknown to the proposed algorithm. But practically the correct correspondence sequence is known. Therefore, the additional part of the proposed algorithm suggests the computation of correspondence which associates the range data to each ultrasonic beacon. The rest of the paper organized as follows. The next section depicts the details of the proposed algorithm. The experiment and performance evaluation of the proposed algorithm discuss in section 3. Finally section 4 gives the conclusion.

2. RESTATEMENT OF UKF LOCALIZATION ALGORITHM

This section discusses the modification in augmented UKF algorithm [4] fusing ultrasonic sensor and laser range including the computation of correspondence for the data association to each beacon.

Altogether we values 23 measurement values, among them we have 4 ultrasonic sensor data, and 19 laser range finder data. As it is impractical to access both of the sensor measurements simultaneously, in this case we have made separate UKF algorithms blocks for each sensor measurements and each UKF block get execute on the availability of respective sensor data. We put a check bit on the processing of each UKF algorithm block. Fig. 1 shows the proposed approach to process the modified UKF algorithm.

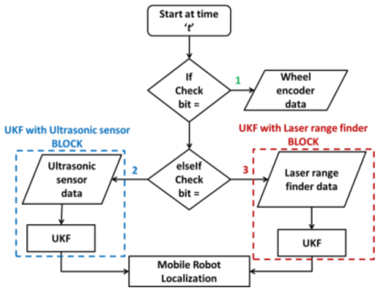

Fig. 1 Flow of modified UKF localization algorithm

2.1 Mean and covariance of State vector

The L dimensionality of the augmented state is given by the sum of state, control and measurement dimensions, which 3+2+N (where N is the number of measurements). The mean μ_{t-1}^{a} of the augmented state estimate is given by the mean of position estimate $\mu_{X,t-1} = (\mu_{x,t-1} \quad \mu_{y,t-1} \quad \mu_{\theta,t-1})$, and zero mean for the control $u_t = (v, \omega)$ and measurements z_t values at time $t-1$ ($\because$ throughout this algorithm the Gaussian noise assume to have zero mean values). Eq. (1) and (2) shows the augmented mean and covariance state matrix for both UKF algorithm blocks.

$$\mu_{t-1}^{a} = \left((\mu_{X,t-1})^T (\mu_v \quad \mu_\omega)^T (\mu_{z_1} \quad \cdots \quad \mu_{z_N})^T \right)$$
$$(\because \ \mu_v, \mu_\omega, \ \mu_{z_1} \cdots \mu_{z_N} = 0 \ ) \tag{1}$$

$$\Sigma_{t-1}^{a} = \begin{bmatrix} \Sigma_{t-1} & 0 & 0 \\ 0 & M_t & 0 \\ 0 & 0 & Q_t \end{bmatrix} \tag{2}$$

Where, M_t and Q_t are the motion noise and measurement noise covariance matrix. Now the augmented mean and covariance matrix are used to generate the sigma points χ_{t-1}^{a} Eq. (3) illustrates the sigma point matrix:

$$\chi_{t-1}^{a} = \left[\mu_{t-1}^{a} \quad \mu_{t-1}^{a} + \gamma\sqrt{(L+\lambda)\Sigma_{t-1}^{a}} \quad \mu_{t-1}^{a} - \gamma\sqrt{(L+\lambda)\Sigma_{t-1}^{a}} \right] \tag{3}$$

Where, $\lambda = \alpha^2(L-\kappa) + L$ is the scaling parameter, α and κ determines spread of sigma points around $\mu_{X,t-1}$. The values of α usually set to 10^{-4}~1 and $\kappa = 0$ [4].

2.2 Prediction Step

The prediction step is same for both UKF algorithm blocks. In the prediction step the location components of the sigma point χ_{t-1}^{x} passes through the motion model "g" along with the control u_t and the added component χ_{t-1}^{u} . This serves as the prediction step for the sigma points, which will be used to calculate the predicted mean and covariance. Eqs.(4)~(6) illustrates the prediction step.

$$\bar{\chi}_{t-1}^{x} = \mathrm{g}\,(u_t + \chi_{t-1}^{u}, \chi_{t-1}^{x}) \tag{4}$$
$$\bar{\mu}_t = \textstyle\sum_{i=0}^{2L} w_i^{(m)}\, \bar{\chi}_{t-1}^{x} \tag{5}$$
$$\bar{\Sigma}_t = \textstyle\sum_{i=0}^{2L} w_i^{(c)}\, (\bar{\chi}_{t-1}^{x} - \bar{\mu}_t)(\bar{\chi}_{t-1}^{x} - \bar{\mu}_t)^T \tag{6}$$

Where $w_i^{(m)}$ and $w_i^{(c)}$ are weights of sigma points [4].

2.3 Correction step

In correction step the predicted robot location components $\bar{\chi}_{t-1}^{x}$ passes through the measurement model "h" and then added with measurement noise sigma points χ_{t-1}^{z}. Eqs. (7)~(10) illustrates the complete correction step.

$$Z_t = h(\bar{\chi}_{t-1}^{x}) + \chi_{t-1}^{z} \tag{7}$$
$$\hat{z}_t = \textstyle\sum_{i=0}^{2L} w_i^{(m)}\, Z_{i,t} \tag{8}$$
$$S_t = \textstyle\sum_{i=0}^{2L} w_i^{(c)}\, (Z_{i,t} - \hat{z}_t)(Z_{i,t} - \hat{z}_t)^T \tag{9}$$
$$\Sigma^{x,z} = \textstyle\sum_{i=0}^{2L} w_i^{(c)}\, (\bar{\chi}_{t-1}^{x} - \bar{\mu}_t)(Z_{i,t} - \hat{z}_t)^T \tag{10}$$

Where, Z_t denotes the measurement sigma points, S_t shows the measurement covariance matrix, and $\Sigma^{x,z}$ computes the cross covariance matrix between predicted state mean $\bar{\mu}_t$ and estimated measurement $\hat{z}_t$.

2.4 Filter update step

The filter update step is virtually identical to the EKF update step [5].

2.5 Computation of correspondence

This subsection states the additional part used in *UKF with ultrasonic sensor block* shown in Fig. 1. This part calculates the correspondence which associates data to ultrasonic beacon. Table 1 shows the pseudo code for the computation of correspondence.

Table 1 Pseudo code for computation of correspondence

For the case of unknown correspondence

1. for Ultrasonic sensor data $z_{k,t}^{U}$
2. for all USAT beacons j in the map $'m'$
3. $\bar{Z}_{t,j}^{U} = (h_U(\bar{\chi}_t^{x}) + \bar{\chi}_t^{z_U})$
4. $\hat{z}_{t,j}^{U} = (\sum_{i=0}^{2L} w_i^{(m)} \bar{Z}_{t,j}^{U})$
5. $S_{t,j}^{U} = (\sum_{i=0}^{2L} w_i^{(c)} (\bar{Z}_{t,j}^{U} - \hat{z}_{t,j}^{U})(\bar{Z}_{t,j}^{U} - \hat{z}_{t,j}^{U})^T)$
6. $ML_j^k = (\det(2\pi S_{t,j}^{U})^{-\frac{1}{2}} \exp\{-\frac{1}{2}(z_{t,k}^{U} - \hat{z}_{t,j}^{U})^T \left[S_{t,j}^{U}\right]^{-1} (z_{t,k}^{U} - \hat{z}_{t,j}^{U})\})$
7. end
8. $c_t^k = \operatorname*{argmax}_k \ (ML)$
9. end

Line 1 runs the "for loop" for all ultrasonic sensor's range data. The variable $z_{k,t}^{U}$ denotes the range data collected from the ultrasonic sensor system the subscript 'k' denotes the number of range data and superscript 'U' used to specify ultrasonic sensor. The inner "for loop" runs to calculate the position of ultrasonic beacons. Line 3~5 shows the correction step. Line 6 computes the probability which maximizes the likelihood of range data for any possible ultrasonic beacon. The variable c_t is correspondence vector and the "argmax" selects the correspondence values for the range data $z_{k,t}^{U}$

3. EXPERIMENT AND PERFORMANCE EVALUATION OF ALGORITHM

3.1 Experiment

The experiment is conducted in a class room. The work space setup for the robot navigation consisting of 6 guided waypoints cluttered with tables, chairs, and the ultrasonic beacons attached on the ceiling of the room. Fig. 2 shows the navigation work space, waypoints and the location of ultrasonic beacons. The green line indicates the real robot trajectory connected with 6 guided way points.

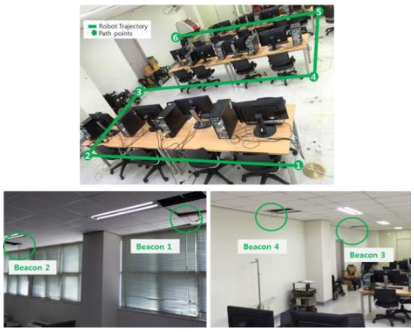

Fig. 2 The robot navigation work space

We use MRP-NRLAB02 differential drive robot manufactured by REDONE Technologies. The robot is equipped with USAT A105 ultrasonic sensor system from the company Korea LPS, and LMS511 of SICK's laser range finder. The robot fed with distance to wall information from the laser range finder and range from beacon to robot provided by ultrasonic receiver. From the navigation experiment, the robot wheel encoder data, range data from ultrasonic sensor system and laser range finder are collected and then saved to the text file.

3.2 Performance evaluation

The collected data set file is access on the MATLAB platform, and we use two different cases of control parameter values to evaluate the performance of the proposed algorithm. The object of evaluation is to verify the localization performance and the computation of correspondences for ultrasonic beacons. Table 2 lists the set of control parameters values.

Table 2 Control parameter values

Case	Motion Noise				Measurement noise	
	α_1	α_1	α_1	α_1	σ_U	σ_{LRF}
1	0.0101	0.033	0.0010	0.11	0.25	0.09
2	0.0103	0.053	0.0012	0.15	0.5	0.1

Fig. 3 shows the estimated trajectory of robot with red line plotted against the real robot trajectory with blue line. Fig. 4 shows the distance error plots. Table 3 lists mean, standard deviation values of distance error, and rate of correct correspondence computation under two cases of control parameter values. Performance evaluation results shows the estimation error of the localization performance decreases and correct correspondence rate increases when appropriate control parameter values are used.

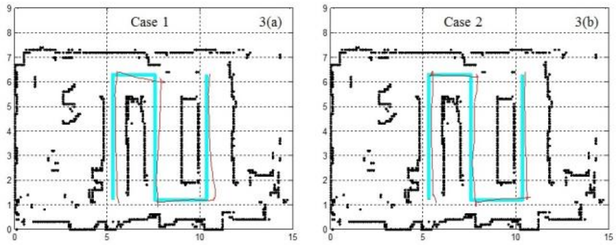

Fig 3 Comparison of estimated trajectories

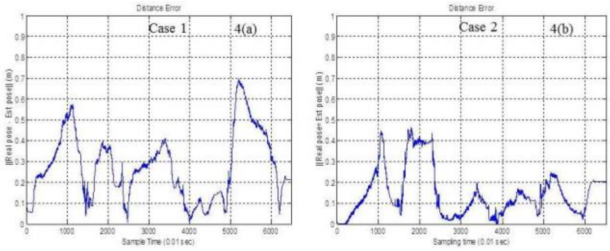

Fig.4 Comparison of distance error between estimated and real robot trajectories

Table 3 Mean, standard deviation of distance error, and rate of correct correspondence computation

Case	Mean	Std dev.	Correct correspondence
1	0.323	0.2227	70.3676%
2	0.2424	0.1434	74.1533%

4. CONCLUSION

The paper shows the implementation of proposed modified UKF algorithm for mobile robot localization in a partially unknown indoor environment. The proposed algorithm result shows assuming appropriate control parameter values causes low estimation error in the localization performance and improve the rate of correct correspondence.

ACKNOWLEDGEMENT

The work was supported by NRF-Grant funded by the Korean Government (NRF-2013-R1A1A4A01-012469).

REFERENCES

[1] E. A. Wan, and R. V. D. Merwe, "The unscented Kalman filter for nonlinear estimation." *Adaptive Systems for Signal Processing, Communications, and Control Symposium*, pp. 153-158, 2000.

[2] S. Naveed, N. Y. Ko, "Analysis of indoor mobile robot localization using ultrasonic sensors," *International Journal of Fuzzy and Intelligent Systems*, Vol. 14, No. 1, pp. 41-48, 2014.

[3] F. Duchon, M. Dekan, L. Jurisica, and A. Vitko, "Some application of laser range finders in mobile robotics," *Journal of Control Engineering and Applied Informatics*, Vol. 14, No. 2, pp. 50-57, 2012.

[4] S. Thrun, W. Burgard, and D. Fox, *Probabilistic*

Robotics, MIT Press, 2005