International Journal of Control, Automation and Systems 15(2) (2017) 947-951
http://dx.doi.org/10.1007/s12555-016-0572-y
ISSN:1598-6446 eISSN:2005-4092
http://www.springer.com/12555

# Extended Least Square Unbiased FIR Filter for Target Tracking Using the Constant Velocity Motion Model

**Jung Min Pak*, Pyung Soo Kim*, Sung Hyun You, Sang Seol Lee, and Moon Kyou Song**

**Abstract:** This paper proposes a new nonlinear state estimator that has a finite impulse response (FIR) structure. The proposed state estimator is called the extended least square unbiased FIR filter (ELSUFF) because it is derived using a least square criterion and has an unbiasedness property. The ELSUFF is a special FIR filter designed for the constant velocity motion model and does not require noise information, such as covariance of Gaussian noise. In situations where noise information is highly uncertain, the ELSUFF can provide consistent performance, while existing nonlinear state estimators, such as the extended Kalman filter (EKF) and the particle filter (PF), often exhibit degraded performance under the same condition. Through simulations, we demonstrate the robustness of the ELSUFF against noise model uncertainty.

**Keywords:** Constant velocity motion model, extended least square unbiased FIR filter (ELSUFF), finite impulse response (FIR) filter, state estimation, target tracking.

## 1. INTRODUCTION

The Kalman filter (KF) is an optimal state estimator for linear systems with Gaussian noise. For state estimation of nonlinear systems, suboptimal state estimators, such as the extended Kalman filter (EKF) and the particle filter (PF), have been widely used [1–4]. Nonlinear suboptimal state estimators have been popularly used for target tracking applications using radar, sonar, and wireless sensor networks (WSNs) [5]. Such applications typically use the state-space model called the constant velocity (CV) motion model, which assumes that targets move with constant velocity (constant speed and course) within a short sampling time. However, real targets maneuver and change speed. Thus, in the CV motion model, the process noise compensates changes in target velocity. Large process noise can compensate large changes in target course, but can worsen estimation accuracy. Thus, the process noise covariance should be carefully selected [6]. A modeling error in the CV model (i.e., mismatch between the real target motion and the CV motion model) leads to degradation of tracking performance or even tracking failures. Therefore, a new nonlinear state estimator that is robust against modeling errors in the CV model is necessary for many target tracking applications.

In this paper, we propose a new nonlinear state estimator that does not require noise information. The proposed state estimator has a finite impulse response (FIR) structure. State estimators with FIR structures are simply called FIR filters [7–11], and they have been studied to overcome divergence phenomena occurring in state estimators with infinite impulse response (IIR) structures. FIR filters are known to be robust against model errors and incorrect noise information [12–16]. In this work, we derived a linear FIR filter that specializes in the CV model, and then we extended the linear FIR filter to nonlinear systems. Because the proposed FIR filter is derived using a least square criterion and has an unbiasedness property, the FIR filter is called the extended least square unbiased FIR filter (ELSUFF). The filter does not require any noise information and is free from the burden of selecting noise covariance when applied to the CV model. The existing nonlinear state estimators, such as the EKF and the PF, may exhibit poor estimation performance or may even di-

Manuscript received September 13, 2016; revised October 21, 2016; accepted November 8, 2016. Recommended by Associate Editor Choon Ki Ahn under the direction of Editor Duk-Sun Shim. This research was supported in part by the MSIP (Ministry of Science, ICT, and Future Planning), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2016-H8601-16-1003) supervised by the IITP (Institute for Information & communication Technology Promotion) and in part by "Human Resources program in Energy Technology" of the Korea Institute of Energy Technology Evaluation and Planning (KETEP) granted financial resource from the Ministry of Trade, Industry & Energy, Republic of Korea (No. 20154030200610).

Jung Min Pak and Sang Seol Lee are with the Department of Electrical Engineering, Wonkwang University, 460 Iksandae-ro, Iksan, Jeonbuk 54538, Korea (e-mails: destin11@wku.ac.kr, slee@wku.ac.kr). Pyung Soo Kim is with the Department of Electronics Engineering, Korea Polytechnic University, 237 Sangideahak-ro, Siheung-si, Gyeonggi-do 15073, Korea (e-mail: pskim@kpu.ac.kr). Sung Hyun You is with the School of Electrical Engineering, Korea University, 145, Anam-ro, Seongbuk-gu, Seoul 02841, Korea (e-mails: ysh88@korea.ac.kr). Moon Kyou Song is with the Department of Electronics Convergence Engineering, Wonkwang University, 460 Iksandae-ro, Iksan, Jeonbuk 54538, Korea (e-mail: mksong@wku.ac.kr).
* Corresponding authors.

Springer
©ICROS, KIEE and Springer 2017

verge due to noise modeling errors. However, the ELSUFF is robust against noise modeling errors and can provide consistent performance regardless of the noise model used. Through simulations of target tracking using the CV model, we demonstrate the robustness of the ELSUFF against noise modeling errors.

## 2. EXTENDED LEAST SQUARE UNBIASED FIR FILTER FOR THE CONSTANT VELOCITY MODEL

Consider the following linear time-varying discrete-time state-space model:

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{G}\mathbf{w}_k, \quad \mathbf{w}_k \sim (0, \mathbf{Q}_k), \tag{1}$$

$$\mathbf{z}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k, \quad \mathbf{v}_k \sim (0, \mathbf{R}_k), \tag{2}$$

where $\mathbf{x}_k \in \Re^p$, $\mathbf{y}_k \in \Re^q$, $\mathbf{w}_k \in \Re^p$, and $\mathbf{v}_k \in \Re^q$ are the state, measurement, and process and measurement noise vectors, respectively. We assume that $\mathbf{A}$ and $\mathbf{G}$ are time invariant, only $\mathbf{C}_k$ is time varying, and $\mathbf{A}$ is nonsingular. The process and measurement noise vectors, $\mathbf{w}_k$ and $\mathbf{v}_k$, are zero-mean white Gaussian with the covariance matrices, $\mathbf{Q}_k$ and $\mathbf{R}_k$, respectively.

Our proposed FIR filter uses recent finite measurements on the time horizon $[m,n]$, where $m = k-N$ and $n = k-1$ are the initial and final time steps of the horizon, $k$ is the current time step, and $N$ is the horizon size. For the system models (1) and (2), the augmented measurement vector, $\mathbf{Z}_n$, can be expressed as a function of current state $\mathbf{x}_k$ as follows:

$$\mathbf{Z}_n = \widetilde{\mathbf{C}}_N\mathbf{x}_k + \widetilde{\mathbf{G}}_N\mathbf{W}_n + \mathbf{V}_n, \tag{3}$$

where

$$\mathbf{Z}_n \triangleq [\mathbf{z}_m^T\ \mathbf{z}_{m+1}^T\ \cdots\ \mathbf{z}_n^T]^T, \tag{4}$$

$$\mathbf{W}_n \triangleq [\mathbf{w}_m^T\ \mathbf{w}_{m+1}^T\ \cdots\ \mathbf{w}_n^T]^T, \tag{5}$$

$$\mathbf{V}_n \triangleq [\mathbf{v}_m^T\ \mathbf{v}_{m+1}^T\ \cdots\ \mathbf{v}_n^T]^T, \tag{6}$$

and $\widetilde{\mathbf{C}}_N$ and $\widetilde{\mathbf{G}}_N$ are given by

$$\widetilde{\mathbf{C}}_N \triangleq \begin{bmatrix} \mathbf{C}_m \\ \mathbf{C}_{m+1}\mathbf{A} \\ \vdots \\ \mathbf{C}_n\mathbf{A}^{N-1} \end{bmatrix} \mathbf{A}^{-N}, \tag{7}$$

$$\widetilde{\mathbf{G}}_N \triangleq -\begin{bmatrix} \mathbf{C}_m\mathbf{A}^{-1} & \mathbf{C}_m\mathbf{A}^{-2} & \cdots & \mathbf{C}_m\mathbf{A}^{-N} \\ \mathbf{0} & \mathbf{C}_{m+1}\mathbf{A}^{-1} & \cdots & \mathbf{C}_{m+1}\mathbf{A}^{-N+1} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{C}_n\mathbf{A}^{-1} \end{bmatrix} \mathbf{G}. \tag{8}$$

The augmented measurement equation (3) can be written as

$$\mathbf{Z}_n - \widetilde{\mathbf{C}}_N\mathbf{x}_k = \widetilde{\mathbf{G}}_N\mathbf{W}_n + \mathbf{V}_n. \tag{9}$$

The left side of above equation, $\mathbf{Z}_{k-1} - \widetilde{\mathbf{C}}_N\mathbf{x}_k$, is the output error (also called the measurement residual), which is required to be minimized. If there is no noise on the time horizon $[m,n]$, the right side of (9) becomes zero and the output error also becomes zero. An FIR filter that minimizes the output error can be obtained by the following least square criterion [7]:

$$\hat{\mathbf{x}}_k = \arg\min_{\mathbf{x}_k}[\mathbf{Z}_n - \widetilde{\mathbf{C}}_N\mathbf{x}_k]^T[\mathbf{Z}_n - \widetilde{\mathbf{C}}_N\mathbf{x}_k]. \tag{10}$$

Following the well-known least square method, the solution of (10) is obtained as

$$\hat{\mathbf{x}}_k = (\widetilde{\mathbf{C}}_N^T\widetilde{\mathbf{C}}_N)^{-1}\widetilde{\mathbf{C}}_N^T\mathbf{Z}_n. \tag{11}$$

In summary, the least square unbiased FIR filter (LSUFF) is described by the following theorem.

**Theorem 1:** When $(\mathbf{A}, \mathbf{C}_k)$ is observable and $N \geq p$, the LSUFF using the recent finite measurement on the time horizon $[m,n]$ is given as

$$\hat{\mathbf{x}}_k = (\widetilde{\mathbf{C}}_N^T\widetilde{\mathbf{C}}_N)^{-1}\widetilde{\mathbf{C}}_N^T\mathbf{Z}_n, \tag{12}$$

where $\widetilde{\mathbf{C}}_N$ and $\mathbf{Z}_n$ are defined in (7) and (8).

Taking expectation on both sides of (12) gives

$$E[\hat{\mathbf{x}}_k] = (\widetilde{\mathbf{C}}_N^T\widetilde{\mathbf{C}}_N)^{-1}\widetilde{\mathbf{C}}_N^T E[\mathbf{Z}_{k-1}]. \tag{13}$$

In (3), the noise term $\widetilde{\mathbf{G}}_N\mathbf{W}_{k-1} + \mathbf{V}_{k-1}$ is zero-mean. Thus, taking expectation on both sides of (3) gives

$$E[\mathbf{Z}_{k-1}] = \widetilde{\mathbf{C}}_N E[\mathbf{x}_k]. \tag{14}$$

Substituting (14) into (13), we obtain

$$\begin{aligned} E[\hat{\mathbf{x}}_k] &= (\widetilde{\mathbf{C}}_N^T\widetilde{\mathbf{C}}_N)^{-1}\widetilde{\mathbf{C}}_N^T\widetilde{\mathbf{C}}_N E[\mathbf{x}_k] \\ &= E[\mathbf{x}_k]. \end{aligned} \tag{15}$$

Because $E[\hat{\mathbf{x}}_k] = E[\mathbf{x}_k]$, the LSUFF has an unbiasedness property.

Now, we extend the LSUFF to nonlinear systems. Consider the following nonlinear state-space model:

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{G}\mathbf{w}_k, \quad \mathbf{w}_k \sim (0, \mathbf{Q}_k), \tag{16}$$

$$\mathbf{z}_k = \mathbf{h}_k(\mathbf{x}_k) + \mathbf{v}_k, \quad \mathbf{v}_k \sim (0, \mathbf{R}_k), \tag{17}$$

where the state equation is linear and only the measurement equation is nonlinear. We can encounter this type of state-space model in many target tracking applications using the CV motion model. To extend the LSUFF to this type of nonlinear system, we linearize the measurement equation. Taylor approximation of (17) gives

$$\begin{aligned} \mathbf{z}_k &\approx \mathbf{h}_k(\hat{\mathbf{x}}_k) + \mathbf{H}_k(\mathbf{x}_k - \hat{\mathbf{x}}_k) + \mathbf{v}_k \\ &= \mathbf{H}_k\mathbf{x}_k + [\mathbf{h}_k(\hat{\mathbf{x}}_k) - \mathbf{H}_k\hat{\mathbf{x}}_k] + \mathbf{v}_k \\ &= \mathbf{H}_k\mathbf{x}_k + \bar{\mathbf{z}}_k + \mathbf{v}_k, \end{aligned} \tag{18}$$

where $\mathbf{H}_k$ and $\bar{\mathbf{z}}_k$ are defined as

$$\mathbf{H}_k \triangleq \left.\frac{\partial \mathbf{h}_k}{\partial \mathbf{x}}\right|_{\hat{\mathbf{x}}_k}, \tag{19}$$

$$\bar{\mathbf{z}}_k \triangleq \mathbf{h}_k(\hat{\mathbf{x}}_k) - \mathbf{H}_k\hat{\mathbf{x}}_k. \tag{20}$$

$\bar{\mathbf{z}}_k$ is not the real measurement signal and can be discarded. However, discarding $\bar{\mathbf{z}}_k$ causes a linearization error. Thus, we utilize $\bar{\mathbf{z}}_k$ as a pseudo measurement signal rather than discarding it. Defining the auxiliary measurement signal as $\tilde{\mathbf{z}}_k = \mathbf{z}_k - \bar{\mathbf{z}}_k$, we obtain a new measurement equation

$$\tilde{\mathbf{z}}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k. \tag{21}$$

Now, we can apply the LSUFF to the nonlinear system models (16) and (21). The ELSUFF, a nonlinear extension of LSUFF, is summarized in the following theorem.

**Theorem 2:** When $(\mathbf{A}, \mathbf{H}_k)$ is observable and $N \le p$, the ELSUFF on the horizon $[m, n]$ is given as

$$\hat{\mathbf{x}}_k = (\widetilde{\mathbf{H}}_N^T \widetilde{\mathbf{H}}_N)^{-1} \widetilde{\mathbf{H}}_N^T \tilde{\mathbf{Z}}_n, \tag{22}$$

where

$$\widetilde{\mathbf{H}}_N = \begin{bmatrix} \mathbf{H}_m \\ \mathbf{H}_{m+1}\mathbf{A} \\ \vdots \\ \mathbf{H}_n\mathbf{A}^{N-1} \end{bmatrix} \mathbf{A}^{-N},$$

$$\tilde{\mathbf{Z}}_n = [\tilde{\mathbf{z}}_m^T \; \tilde{\mathbf{z}}_{m+1}^T \; \cdots \; \tilde{\mathbf{z}}_n^T]^T. \tag{23}$$

## 3. NUMERICAL EXAMPLE

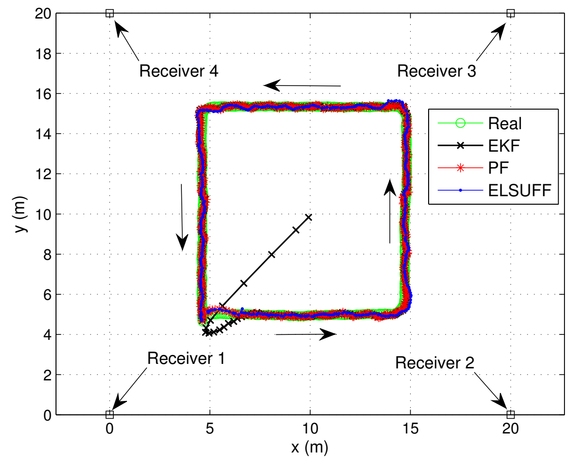
In this section, we present a numerical example to demonstrate performance of the proposed ELSUFF. In a typical target tracking application using the CV model, we compare the ELSUFF with well-known nonlinear filters such as the EKF and the PF.

Consider an indoor localization system based on a WSN as shown in Fig. 1(a). A wireless tag (transmitter) is attached to a target object, which can be human or equipment. The WSN is composed of four receivers and a server computer and provides time difference of arrival (TDOA) measurements. The state-space model for the indoor localization system has a linear motion model (CV model) and nonlinear measurement model based on TDOA measurement.

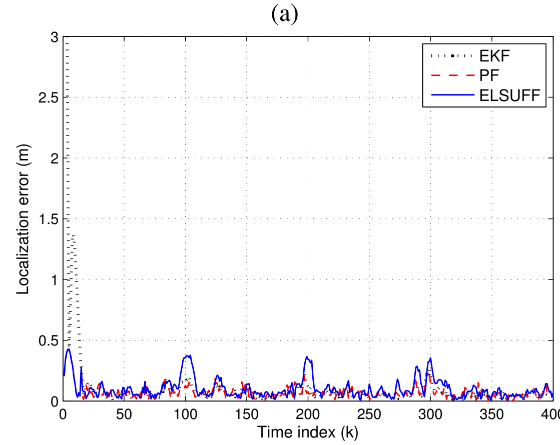
Introducing a state vector that describes the target's 2D positions and velocities, $\mathbf{x}_k = [x_k \; y_k \; \dot{x}_k \; \dot{y}_k]^T$, the CV motion model can be described as

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{G}\mathbf{w}_k, \tag{24}$$

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{G} = \begin{bmatrix} T^2/2 & 0 \\ 0 & T^2/2 \\ T & 0 \\ 0 & T \end{bmatrix}, \tag{25}$$




(a)




(b)

Fig. 1. Localization results when $\mathbf{Q}_k = I_2$: (a) real and estimated trajectories, and (b) localization errors.

where $T$ is the sampling interval and $\mathbf{A}$ is always nonsingular regardless of the value of $T$.

In turn, the TDOA measurement model can be described as

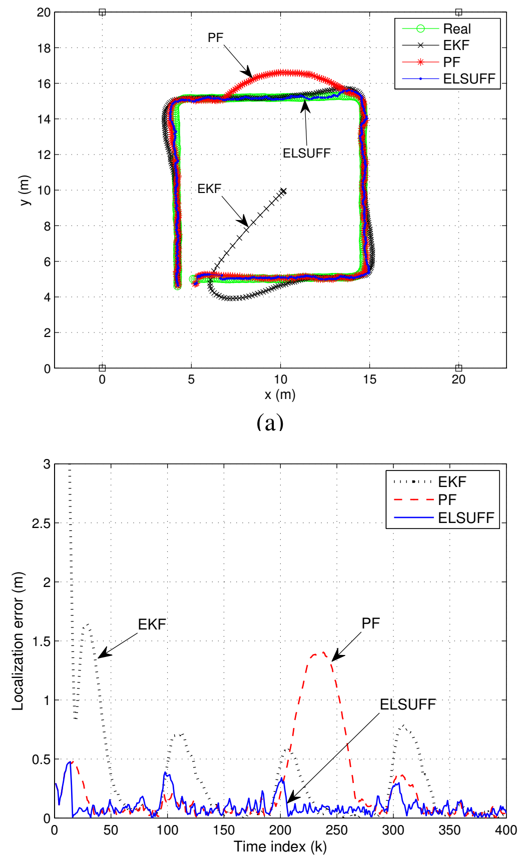
$$\mathbf{z}_k = \begin{bmatrix} z_{1,k} \\ z_{2,k} \\ z_{3,k} \end{bmatrix} = \begin{bmatrix} h_{1,k} \\ h_{2,k} \\ h_{3,k} \end{bmatrix} = \frac{1}{c}\begin{bmatrix} d_1 - d_2 \\ d_1 - d_3 \\ d_1 - d_4 \end{bmatrix}, \tag{26}$$

where

$$d_i = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2}, \tag{27}$$

and $c$ is speed of light, $\mathbf{v}_k \in \Re^3$ is a zero-mean Gaussian measurement noise with the covariance $\mathbf{R}_k$.

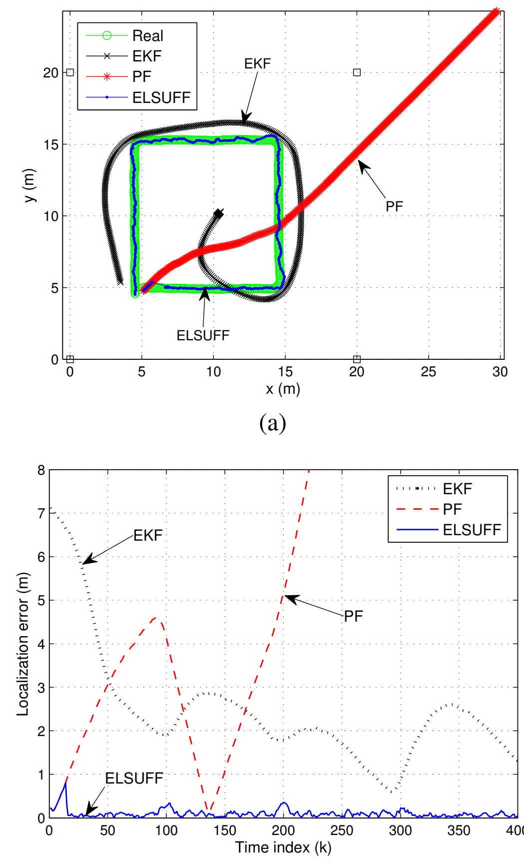
Using the state-space models (24) and (26), we can apply the nonlinear state estimators. A scenario for the indoor localization simulation is as follows. A target with a transmitter starts from the position $(5,5)$ and moves counterclockwise along a rectangular trajectory as shown in Fig. 1(a). We estimate the target's positions by processing the TDOA measurements using the nonlinear state estimators including the EKF, the PF, and the ELSUFF. The




(a)

(b)

Fig. 2. Localization results when $\mathbf{Q}_k = 1\times10^{-2}I_2$: (a) real and estimated trajectories, and (b) localization errors.




(a)

(b)

Fig. 3. Localization results when $\mathbf{Q}_k = 1\times10^{-4}I_2$: (a) real and estimated trajectories, and (b) localization errors.

initial position of the target is assumed to be unknown. In the simulations, we use 1000 particles for the PF. Horizon size for the ELSUFF is taken as $N = 14$. The measurement noise covariance is set as $\mathbf{R}_k = 0.5I_3$ in every simulation, and $I_n$ denotes an $n\times n$ identity matrix.

Fig. 1 shows the localization results when we set the process noise covariance as $\mathbf{Q}_k = I_2$. In this case, all three nonlinear state estimators (i.e., EKF, PF, and ELSUFF) work successfully and exhibit localization errors smaller than $0.5\,m$ during most of the simulation time. The total operation times (in seconds) of the EKF, PF, ELSUFF are 0.025, 10.3, and 0.75, respectively. In terms of the computational efficiency, the ELSUFF is superior to the PF and inferior to the EKF.

Fig. 2 shows the localization results obtained using $\mathbf{Q}_k = 1\times10^{-2}I_2$. We can see that both the EKF and the PF show degraded localization accuracy compared to that in Fig. 1. The localization performances of the EKF and the PF are especially degraded around the corners of the rectangular trajectory, which can be observed around the time indices $k = 100$, $k = 200$, and $k = 300$ in Fig. 2(b).

The target abruptly changes its course at the corners, and these abrupt motion changes lead to modeling errors (i.e., mismatches between the CV model and the real motion) and degraded localization accuracy. $\mathbf{Q}_k$ is related to the amount of motion change in the CV model. If $\mathbf{Q}_k$ is small compared with the real motion change, state estimators may exhibit degraded performance. Thus, the EKF and the PF showed poor performance in the simulation with $\mathbf{Q}_k = 1\times10^{-2}I_2$. However, the ELSUFF does not require information on $\mathbf{Q}_k$ and does not suffer from the performance degradation caused by an incorrectly selected $\mathbf{Q}_k$. In short, the simulation results demonstrate the robustness of the ELSUFF against noise modeling errors.

The robustness of the ELSUFF is demonstrated again in Fig. 3, which shows the localization results with $\mathbf{Q}_k = 1\times10^{-4}I_2$. The EKF exhibits poor localization accuracy, and the PF diverges. The PF divergence is, in part, owing to sample impoverishment, which occurs when the process noise is small. In contrast to the EKF and the PF, the ELSUFF successfully works and provides satisfactory localization results under the same condition.

Table 1 compares the three state estimators in terms of localization accuracy in various cases of $\mathbf{Q}_k$. For differ-

Table 1. Average localization errors of EKF, PF, and ELSUFF for different values of $\mathbf{Q}_k$.

| $\mathbf{Q}_k$ | EKF | PF | ELSUFF |
|---|---|---|---|
| $I_2$ | 0.2560 | 0.2505 | 0.2984 |
| $1\times10^{-1}I_2$ | 0.3384 | 0.2607 | 0.2984 |
| $1\times10^{-2}I_2$ | 0.5356 | 0.5368 | 0.2984 |
| $1\times10^{-3}I_2$ | 0.9731 | 3.2568 | 0.2984 |
| $1\times10^{-4}I_2$ | 1.5365 | 3.3728 | 0.2984 |

ent values of $\mathbf{Q}_k$, we conducted Monte-Carlo (MC) simulations to obtain average localization errors. Each value in Table 1 was obtained through 100 MC runs. When $\mathbf{Q}_k = I_2$, the EKF and the PF work successfully and exhibit better performance than the ELSUFF. However, decreasing $\mathbf{Q}_k$ degrades performance of the EKF and PF due to mismatch between the real motion and the CV model. On the contrary, the ELSUFF exhibits consistent performance, which demonstrates robustness of the ELSUFF against noise modeling error.

## 4. CONCLUSIONS

In this paper, we proposed a new nonlinear state estimator called the ELSUFF, which has an FIR structure and an unbiasedness property. The existing nonlinear state estimators, such as the EKF and the PF, may exhibit degraded performance if the process and measurement noise are modeled incorrectly. However, the proposed ELSUFF does not require noise information and can provide consistent performance if noise information is uncertain. Through indoor localization simulations, we demonstrated the robustness of the ELSUFF against noise modeling errors. Thus, the ELSUFF is expected to be effective in many tracking applications using the CV model in which the noise information is highly uncertain. However, the ELSUFF is applicable only to systems with nonsingular system matrices. Therefore, development of an advanced ELSUFF that is applicable to general nonlinear systems is necessary and will be the focus of our future work.

## REFERENCES


[1] J. Kim, K. Cho, and S. Choi, "Lumped disturbance compensation using extended Kalman filter for permanent magnet linear motor system," *International Journal of Control, Automation, and Systems*, vol. 14, no. 5, pp. 1244-1253, Oct. 2016. [click]

[2] P. S. Pratama, A. V. Gulakari, Y. D. Setiawan, D. H. Kim, H. K. Kim, and S. B. Kim, "Trajectory tracking and fault detection algorithm for automatic guided vehicle based on multiple positioning modules," *International Journal of Control, Automation, and Systems*, vol. 14, no. 2, pp. 400-410, Apr. 2016. [click]

[3] H. Li and Y. Shi, "Robust distributed model predictive control of constrained continuous-time nonlinear systems: A robustness constraint approach," *IEEE Trans. on Automatic Control*, vol. 59, no. 6, pp. 1673-1678, Jun. 2014.

[4] —, "Distributed receding horizon control of large-scale nonlinear systems: Handling communication delays and disturbances," *Automatica*, vol. 50, no. 4, pp. 1264-1271, Apr. 2014. [click]

[5] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning technique and systems," *IEEE Trans. on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 37, no. 6, pp. 1067-1080, Nov. 2007.

[6] B. F. L. Scala and R. R. Bitmead, "Design of an extended Kalman filter frequency tracker," *IEEE Trans. on Signal Processing*, vol. 44, no. 3, pp. 739-742, Mar. 1996.

[7] P. S. Kim and M. E. Lee, "A new FIR filter for state estimation and its application," *Journal of Computer Science and Technology*, vol. 22, no. 5, pp. 779-784, Sep. 2007. [click]

[8] C. K. Ahn, S. Han, and W. H. Kwon, "$H_\infty$ FIR filters for linear continuous-time state-space systems," *IEEE Signal Processing Letters*, vol. 13, no. 9, pp. 557-560, Sep. 2006.

[9] C. K. Ahn, "A new solution to the induced $l_\infty$ finite impulse response filtering problem based on two matrix inequalities," *International Journal of Control*, vol. 87, no. 2, pp. 404-409, Feb. 2014.

[10] C. K. Ahn, P. Shi, and M. V. Basin, "Two-dimensional dissipative control and filtering for Roesser model," *IEEE Trans. on Automatic Control*, vol. 60, no. 7, pp. 1745-1759, Jul. 2015.

[11] —, "Deadbeat dissipative FIR filtering," *IEEE Trans. on Circuits and Systems-I: Regular Papers*, vol. 63, no. 8, pp. 1210-1221, Aug. 2016.

[12] J. M. Pak, C. K. Ahn, M. T. Lim, and M. K. Song, "Horizon group shift FIR filter: Alternative nonlinear filter using finite recent measurements," *Measurement*, vol. 57, pp. 33-45, Nov. 2014. [click]

[13] J. M. Pak, C. K. Ahn, Y. S. Shmaliy, and M. T. Lim, "Improving reliability of particle filter-based localization in wireless sensor networks via hybrid particle/FIR filtering," *IEEE Trans. on Industrial Informatics*, vol. 11, no. 5, pp. 1089-1098, Oct. 2015.

[14] J. M. Pak, C. K. Ahn, Y. S. Shmaliy, P. Shi, and M. T. Lim, "Switching extensible FIR filter bank for adaptive horizon state estimation with application," *IEEE Trans. on Control Systems Technology*, vol. 24, no. 3, pp. 1052-1058, May 2016.

[15] J. M. Pak, C. K. Ahn, P. Shi, Y. S. Shmaliy, and M. T. Lim, "Distributed hybrid particle/FIR filtering for mitigating NLOS effects in TOA-based localization using wireless sensor networks," *IEEE Trans. on Industrial Electronics, to be published, doi: 10.1109/TIE.2016.2608897*.

[16] J. M. Pak, C. K. Ahn, Y. S. Shmaliy, P. Shi, and M. T. Lim, "Accurate and reliable human localization using composite particle/FIR filtering," *IEEE Trans. on Human-Machine Systems, to be published, doi: 10.1109/THMS.2016.2611826*.