

Adaptive Wireless Localization Filter Containing NLOS Error Mitigation Function

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ABSTRACT

Range-based wireless localization system must measure accurate range between a mobile node (MN) and reference nodes. However, non-line-of-sight (NLOS) error caused by the spatial structures disturbs the localization system obtaining the accurate range measurements. Localization methods using the range measurements including NLOS error yield large localization error. But filter-based localization methods can provide comparatively accurate location solution. Motivated by the accuracy of the filter-based localization method, a filter residual-based NLOS error estimation method is presented in this paper. Range measurement-based residual contains NLOS error. By considering this factor with NLOS error properties, NLOS error is mitigated. Also a process noise covariance matrix tuning method is presented to reduce the time-delay estimation error caused by the single dynamic model-based filter when the speed or moving direction of a MN changes, that is the used dynamic model is not fit the current dynamic of a MN. The presented methods are evaluated by simulation allowing direct comparison between different localization methods. The simulation results show that the presented filter is more accurate than the iterative least squares- and extended Kalman filter-based localization methods.

Keywords: wireless localization, range measurement, NLOS error, estimation filter, residual, single dynamic model

1. INTRODUCTION

Accurate mobile node (MN) localization for pedestrians has been an investigational hot potato in the last two decades owing to emergence of location based service (LBS) market. Several solutions have been used through global positioning system (GPS), cellular, and other wireless networks. Actually, GPS can provide accurate location solution in open area. In indoor and urban area, however, GPS is not to be a sure method due to signal blockage or signal pollution. Cellular signal can be used in both indoor and outdoor space for MN localization. But cellular signal-based localization solution cannot be used for accurate LBSs such as road guidance, navigation for a blind, etc. because of its inaccuracy. For accurate localization of a MN, several wireless networks such as ultra wideband, chirp

spread spectrum (CSS), ultrasonic wave, etc. have been adopted (Kolodziej & Hjelm 2006, Cho & Kim 2013).

To localize a MN in a wireless network, one or a combination of range measurements, angle measurements and signal strength measurements obtained from time-of-arrival round-trip-of-flight time-difference-of-arrival, angle-of-arrival, and received signal strength indicator approaches can be used with reference nodes (RN) whose location is known. This work is a result of research on the range measurement-based localization method.

Various localization methods can be classified according to use of a model-based filter, that is filter-free localization method (FfLM) (Huang et al. 2001, Cheung et al. 2006, Cho & Kim 2013, Cho et al. 2013) and filter-based localization method (FbLM) (Lee et al. 2004, Huerta & Vidal 2009, Banani et al. 2013). FfLMs include several iterative methods and linear closed-form solution methods. These methods can provide accurate location solution if the range measurements do not include any error terms. In real environments, however, the range measurements contain several error terms including non-line-of-sight

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(NLOS) error. Therefore, the FfLM cannot estimate accurate location and walking trajectory of a pedestrian possessing a MN in real indoor or urban area. On the other hand, the FbLM can estimate comparatively accurate location in NLOS situations as compared with the FfLM (Banani et al. 2013). The reason is that the FbLM estimates the location solution based on the current dynamic model of a MN and measurement, while the FfLM does that only based on the measurement. The dynamic model can reduce the effect of the NLOS error in the measurement. Therefore, the jump error caused by the NLOS error in the FbLM is smaller than the FfLM. This factor supports the main idea of this paper.

In some of the conventional localization methods, it has been assumed that the range measurements consist of LOS propagation and additive white Gaussian noise (AWGN) (Huang et al. 2001, Cheung et al. 2006, Cho & Kim 2013, Cho et al. 2013). However, this idealized case does not occur in typical real environment. So, there's no help for performance reduction when these methods are used in NLOS situations. Different approaches have been investigated for performance improvement. For example, the measurement error is modeled as the addition of a bias and AWGN (Najar et al. 2004, Lin & Pingzhi 2006). The bias error is then augmented in the state variables of a filter. Another approach is that NLOS error distribution is modelled as additive Rayleigh (Huerta & Vidal 2009). In this approach, NLOS error is also augmented in the state variables to be estimated in a filter. In some other approaches, the range measurement is modeled as the sum of a line-of-sight (LOS) component, AWGN and NLOS error designed using multipath scattering model (Al-Jazzar et al. 2002, Kong 2009, Banani et al. 2013). In more approach, NLOS error is treated as a measurement fault (Sturza & Brown 1990, Lee et al. 2004). Then, a method for detecting the jump and ramp errors caused by NLOS errors is presented. Based on the designed NLOS error model, it has been tried to estimate the measurement error for accurate localization in NLOS situations. However, it is difficult to design NLOS error exactly.

In this paper, a novel FbLM is presented to mitigate the NLOS error. This method does not rely on the NLOS error model except that NLOS error has a positive real value at all times. The main idea of this method is from the concept of differential GPS (DGPS) (Farrell & Barth 1999). In reference stations of which locations are known, the measurement errors including NLOS error can be estimated based on the known location information of the reference stations. In the applications of wireless localization, however, it is impossible to set up a mobile reference station in a MN without additional accurate reference localization system.

This technical barrier can be weakened by the advantage of the FbLM, that is the localization result of the FbLM can be used as the reference solution of a reference station. From this, it can be expected that the channel-wise NLOS error can be estimated using the residual of the localization filter. Consequently, NLOS error in the range measurement can be mitigated. This is the first contribution of this paper.

The system model of the localization Filter must fit the representation of a pedestrian's motions such as being stationary, walking or running in a straight line with constant velocity, accelerating, making a turn, etc. for all of the time. Therefore, a single dynamic model cannot represent all of the motions. In target tracking applications, an interacting multiple model (IMM) filter has been used (Bar-Shalom et al. 2005). In (Banani et al. 2013), model selection algorithm for two dynamic models is presented. However, the accelerating/decelerating/turning time of a pedestrian is short and a pedestrian's motion is comparatively slow in the generality of cases. From this fact, a single model called the constant velocity model is adopted for the system model in the localization filter in this paper. When a target pedestrian makes turns or changes walking speeds, the estimation error of the localization filter may be increased. That's driving residual of the filter high. By detecting the residual's growth, in this paper, the process noise covariance matrix is set as a bigger value. This means that the current filter more trusts the measurement than the filter dynamic model. That is, the change of the pedestrian's motion is reflected in the localization filter with a single model. This is the second contribution of this paper.

The performance of the presented method is evaluated by simulation. In the simulation, the result of the presented method is compared with the iterative least squares (ILS) method representing the FfLMs and the extended Kalman filter (EKF) representing the FbLMs. Also, it is shown that the performance of the presented method is more accurate than the conventional methods.

The rest of the paper is organized as follows. Section 2 describes the EKF-based wireless localization with range measurement. The two-step EKF-based enhance wireless localization is presented in Section 3 with the simulation results in Section 4. Finally, Section 5 gives conclusions.

2. EKF-BASED WIRELESS LOCALIZATION WITH RANGE MEASUREMENT

2.1 Range Measurement

The Euclidean range measurement r_k^j in 2-dimensional

space between a mobile node and j -th RN at the k -th epoch can be modeled by

$$\begin{aligned}\tilde{r}_k^j &= r_k^j + \delta_k^j + u_k^j \\ &= \sqrt{(x^j - x_k^m)^2 + (y^j - y_k^m)^2} + \delta_k^j + u_k^j\end{aligned}\quad (1)$$

where r_k^j indicates the true range, $(\tilde{\cdot})$ indicates the measurement of (\cdot) , (x^j, y^j) and (x_k^m, y_k^m) indicate location data of the j -th RN and MN, respectively, u_k^j indicates measurement noise which is assumed as a zero mean stationary Gaussian random process, and δ_k^j indicates non-Gaussian error caused by multipath and NLOS signals and is called as NLOS error in this paper. NLOS error occurs when direct signal paths between MN and RNs are mostly obstructed by some structures. Therefore, NLOS error is always positive real value.

2.2 Filter-based Localization Method

It is difficult to design a single model representing pedestrian's motions for all of the time. However, the accelerating/decelerating/turning time of a pedestrian is short and a pedestrian's motion is comparatively slow in the generality of cases. Therefore, the constant velocity model can be selected as the representing model of a pedestrian's motions. The constant velocity model is described as (Li & Jilkov 2003, Banani et al. 2013)

$$\begin{aligned}X_{k+1} &= FX_k + w_k \\ \Leftrightarrow \begin{bmatrix} x_{k+1}^m \\ \dot{x}_{k+1}^m \\ y_{k+1}^m \\ \dot{y}_{k+1}^m \end{bmatrix} &= \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_k^m \\ \dot{x}_k^m \\ y_k^m \\ \dot{y}_k^m \end{bmatrix} + w_k\end{aligned}\quad (2)$$

where T denotes the location sampling duration. Also, it can be set equal to the range measurement taking period. X denotes the state vector, \dot{u} denotes the velocity state variable of u , F denotes the system matrix, and w_k denotes the process noise which has a zero-mean white Gaussian noise with the covariance matrix Q .

As shown in Eq. (1), the range measurement equation is nonlinear. In this paper, therefore, the EKF is used. Measurement equation can be designed as

$$\begin{aligned}z_k &= H_k \delta X_k + v_k \\ &= \begin{bmatrix} -\frac{x^1 - \hat{x}_k^m}{\hat{r}_k^1} & 0 & -\frac{y^1 - \hat{y}_k^m}{\hat{r}_k^1} & 0 \\ \vdots & \vdots & \vdots & \vdots \\ -\frac{x^n - \hat{x}_k^m}{\hat{r}_k^n} & 0 & -\frac{y^n - \hat{y}_k^m}{\hat{r}_k^n} & 0 \end{bmatrix} \delta X_k + v_k\end{aligned}\quad (3)$$

where δX denotes the error state vector for EKF, n denotes the number of RNs, H denotes the measurement matrix, v_k is the measurement noise which has a zero-mean white Gaussian noise with the following covariance matrix

$$R = \text{diag}(\overbrace{(\alpha)^2 \cdots (\alpha)^2})^n \quad (4)$$

where α denotes the standard deviation of the range measurement noise. α depends on the PHY characteristics of wireless communication infra used for measuring the range between a MN and RNs.

In Eq. (3), \hat{r}_k^j is the range data estimated using the current localization solution as

$$\hat{r}_k^j = \sqrt{(x^j - \hat{x}_k^m)^2 + (y^j - \hat{y}_k^m)^2} \quad (5)$$

Based on the system and measurement matrices designed in Eqs. (2) and (3), the following EKF procedure is iterated whenever a set of range measurements is obtained (Brown & Hwang 1997).

Kalman gain calculation:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R)^{-1} \quad (6)$$

where P_k^- denotes the time propagated state error covariance matrix.

Measurement update:

$$\hat{X}_k = \hat{X}_k^- + K_k \zeta_k \quad \text{and} \quad (7)$$

$$P_k = (I_{4 \times 4} - K_k H_k) P_k^- \quad (8)$$

where \hat{X}_k^- denotes the time propagated state vector, P_k denotes state error covariance matrix at the k -th epoch, $I_{4 \times 4}$ denotes a 4x4 identity matrix, and ζ_k denotes a residual vector calculated as

$$\zeta_k = \begin{bmatrix} \tilde{r}_k^1 - \hat{r}_k^1 \\ \vdots \\ \tilde{r}_k^n - \hat{r}_k^n \end{bmatrix} \quad (9)$$

Time propagation:

$$P_{k+1}^- = F P_k^- F^T + Q \quad \text{and} \quad (10)$$

$$\hat{X}_{k+1}^- = F \hat{X}_k^- \quad (11)$$

Instead of the EKF, various nonlinear filters can be used such as unscented Kalman filter, particle filter, etc.

It is difficult to consider the NLOS error as one of state variables to be estimated in the FbLMs because the NLOS error has a temporally uncorrelated property. However the effect of the NLOS error in the FbLMs may be reduced by

relying on the filter dynamic model. The smaller the process noise covariance matrix is set, the higher the dependence on the filter dynamic model becomes. When the speed or walking direction of the test personnel changes rapidly, however, the estimates of the filter have no choice but to have time-delay errors. Therefore, it is important to set the process noise covariance matrix properly in the single model-based filter.

3. ADAPTIVE FILTER-BASED ENHANCED WIRELESS LOCALIZATION

3.1 NLOS Error Mitigation using Filter Residual

Eq. (5) can be expanded as

$$\begin{aligned} \hat{r}_k^j &= \sqrt{(x^j - (x_k^m + \delta x_k^m))^2 + (y^j - (y_k^m + \delta y_k^m))^2} \\ &\cong r_k^j - \left\{ \frac{x^j - x_k^m}{r_k^j} \delta x_k^m + \frac{y^j - y_k^m}{r_k^j} \delta y_k^m \right\} \\ &\cong r_k^j - \varepsilon_k^j \end{aligned} \tag{12}$$

where $[\delta x_k^m, \delta y_k^m]^T$ is the location estimation error, ε_k^j is the range estimation error caused by the location estimation error, and r_k^j is the error free range data.

By substituting Eqs. (1, 12) into Eq. (9), the residual vector of the filter can be represented in detail as

$$\begin{aligned} \zeta_k &= \begin{bmatrix} \tilde{r}_k^1 \\ \vdots \\ \tilde{r}_k^n \end{bmatrix} - \begin{bmatrix} \hat{r}_k^1 \\ \vdots \\ \hat{r}_k^n \end{bmatrix} \\ &= \begin{bmatrix} r_k^1 + \delta_k^1 + u_k^1 \\ \vdots \\ r_k^n + \delta_k^n + u_k^n \end{bmatrix} - \begin{bmatrix} r_k^1 - \varepsilon_k^1 \\ \vdots \\ r_k^n - \varepsilon_k^n \end{bmatrix} \\ &= \begin{bmatrix} \delta_k^1 \\ \vdots \\ \delta_k^n \end{bmatrix} + \begin{bmatrix} \varepsilon_k^1 \\ \vdots \\ \varepsilon_k^n \end{bmatrix} + \begin{bmatrix} u_k^1 \\ \vdots \\ u_k^n \end{bmatrix} \\ &\cong N_k + E_k + U_k \end{aligned} \tag{13}$$

where N_k denotes the channel-wise NLOS error vector contained in the measurement vector, E_k denotes the channel-wise range estimation error vector caused by the location estimation error, and U_k denotes the channel-wise measurement noise vector.

The sequence of U_k has a zero-mean Gaussian noise property and the measurement error covariance matrix in the filter is in charge of it. If the location error state in the filter is observable, E_k may converge into a zero vector with time. In the residual vector, of course, the range

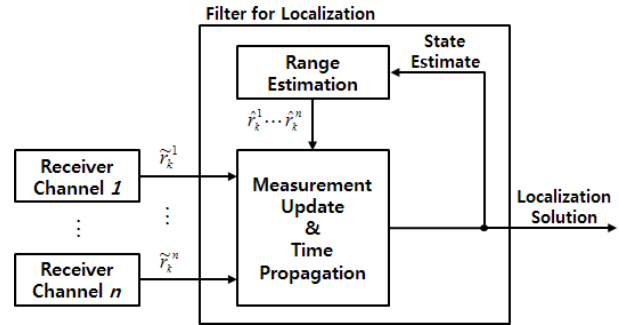


Fig. 1. System structure that utilize the channel-wise NLOS error mitigation method in epoch-by-epoch localization.

estimation error cannot be disappeared. However, the effect of the NLOS error in the filter may be reduced by relying on the filter model as mentioned in the previous Section. So, it is assumed that E_k can be ignored in this paper. By considering the NLOS error property that is always positive real value, consequently, the channel-wise NLOS error can be estimated using the filter residual vector as follows:

$$\hat{\delta}_k^j = \begin{cases} |\zeta_k^j|, & |\zeta_k^j| > \alpha \\ 0, & |\zeta_k^j| \leq \alpha \end{cases} \tag{14}$$

where $j=1,2,\dots,n$, and α is determined in the light of the PHY characteristics of wireless communication infra.

That is, if the channel-wise residual is small than the standard deviation of the range measurement noise, the NLOS error estimate is set equal to zero by considering U_k in Eq. (13), unless, the NLOS error is estimated as the absolute value of the filter residual.

Fig. 1 shows the system structure utilizing the channel-wise NLOS error mitigation method in epoch-by-epoch localization. The residual vector is compensated before the measurement update of the state vector as

$$\tilde{\zeta}_k = \zeta_k - \begin{bmatrix} \hat{\delta}_k^1 \\ \vdots \\ \hat{\delta}_k^n \end{bmatrix} \tag{15}$$

Eq. (7) is replaced by

$$\hat{X}_k = \hat{X}_k^- + K_k \tilde{\zeta}_k. \tag{16}$$

3.2 Process Noise Covariance Matrix Tuning using Filter Residual

Here, the goal is to tune the process noise covariance matrix for estimating the best location for time sample k . In this paper, a single constant velocity model is used in the localization filter. When the speed or walking direction of the test personnel changes rapidly, the estimates of the filter

have no choice but to have time-delay errors because of using the single model. However, it can be seen in Eq. (13) that the filter must provide location solution as accurate as possible for estimating the NLOS error accurately using the filter residual. For this, the filter residual is reused in this paper after mitigating the NLOS error.

When time-delay errors occur in the filter, in the residual contains the effect. That is, the rapid change of the speed or walking direction of the test personnel can be confirmed by checking the following Euclidean distance of the residual vector (EDRV).

$$\xi_k = \sqrt{\hat{z}_k^T \hat{z}_k} \quad (17)$$

Based on the EDRV, the process noise covariance matrix is changed as follows:

$$Q_k = \gamma \cdot Q \quad (18)$$

where γ is set equal to ξ_k^2 if ξ_k is larger than a threshold(β) which is set heuristically, unless γ is set equal to 1.

If γ is set equal to ξ_k , the filter more relies on the measurement than the model. As a result, the change of the state variables can be estimated rapidly.

4. PERFORMANCE EVALUATION

In order to evaluate the performance of the proposed adaptive filter-based enhanced wireless localization method, simulation was performed. An example scenario that has typical characteristics of a pedestrian’s motion, is used for demonstrating the localization performance. The working space is 100 m × 100 m with four RNs at the corners, that is at (0.01, 0.01), (100.0, 0.01), (100.0, 100.0) and (0.01, 100.0) m. It is assumed that the PHY of wireless communication infra

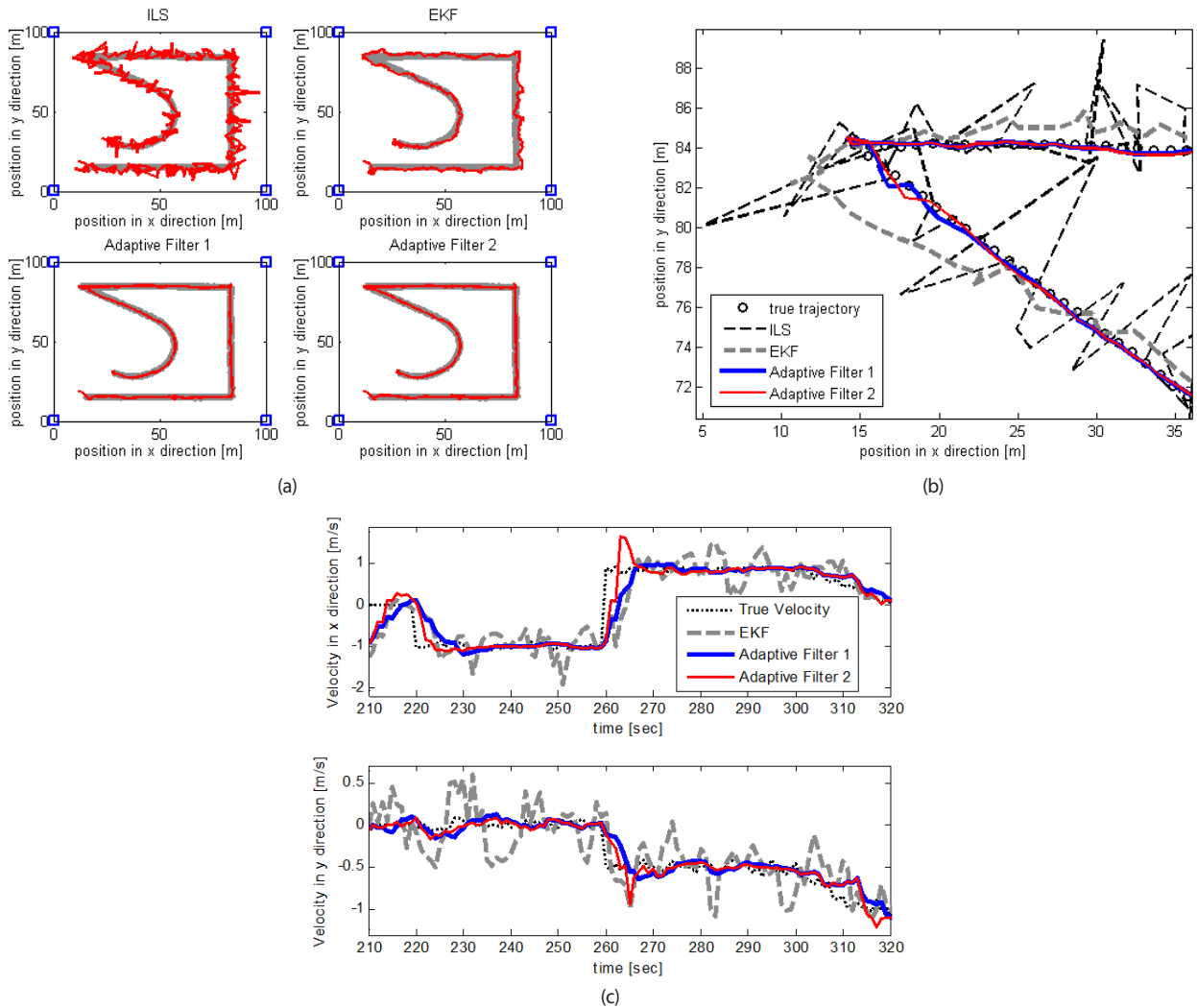


Fig. 2. True trajectory of a mobile node, instantaneously estimated locations and velocities using the ILS, EKF, presented adaptive filter 1 and presented adaptive filter 2. (a) estimated locations (b) expanded figure of the estimated locations

is CSS that has good ranging performance. Based on the PHY characteristics of CSS, the error of the range measurements and NLOS error were set as

$$u_k^i = randn/3.0 \text{ and} \tag{19}$$

$$\delta_k^j = \begin{cases} 0.0, & \lambda < 2.0 \\ \lambda, & \text{otherwise} \end{cases}, \lambda = 5.0 \cdot randn \tag{20}$$

where *randn* denotes a normally distributed random number with zero mean and covariance 1.

The range measurement is generated according to the above errors. All the simulations use $\alpha = 1.0$, $\beta = 1.5$ and $T = 1.0s$. The units of the position and velocity in each direction of the 2D Cartesian coordinate are measured in m and m/s, respectively. The presented filters and the EKF are initialized by the ILS method at the first epoch.

The true trajectory of a MN, along with an instantaneous estimation of locations and velocities of the MN are illustrated in Fig. 2. As shown in this figure, the trajectory consists of standstill, constant velocity, making a turn, etc. Therefore, it is difficult to describe the motion of a MN by using a single dynamic model. Under these circumstances, the ILS method causes large errors by reflecting the NLOS errors intactly because it estimates the locations only using the measurements without any model, as shown in Fig. 2. The EKF-based localization method, on the other hand, yields the error reduced location solutions in spite of the NLOS error presence, compared with the ILS method.

The adaptive filter 1 estimates / compensates the NLOS error using the filter residual and the adaptive filter 2 tunes the process noise covariance matrix using the residual of the adaptive filter 1. Fig. 2b shows that the presented

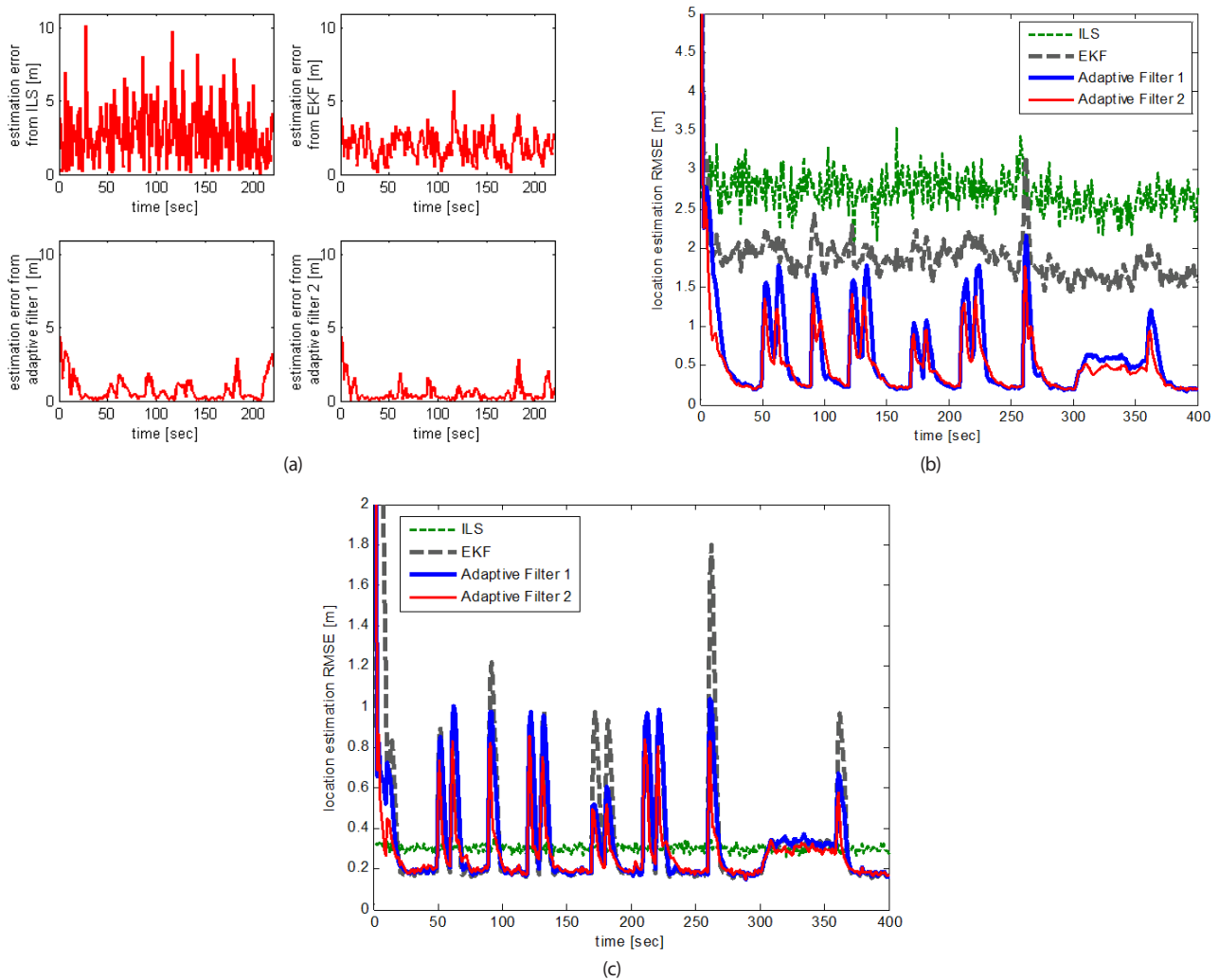


Fig. 3. Comparison of the estimated locations using different localization methods. (a) location estimation error (b) RMSE of the estimated location (c) RMSE of the estimated location without NLOS error.

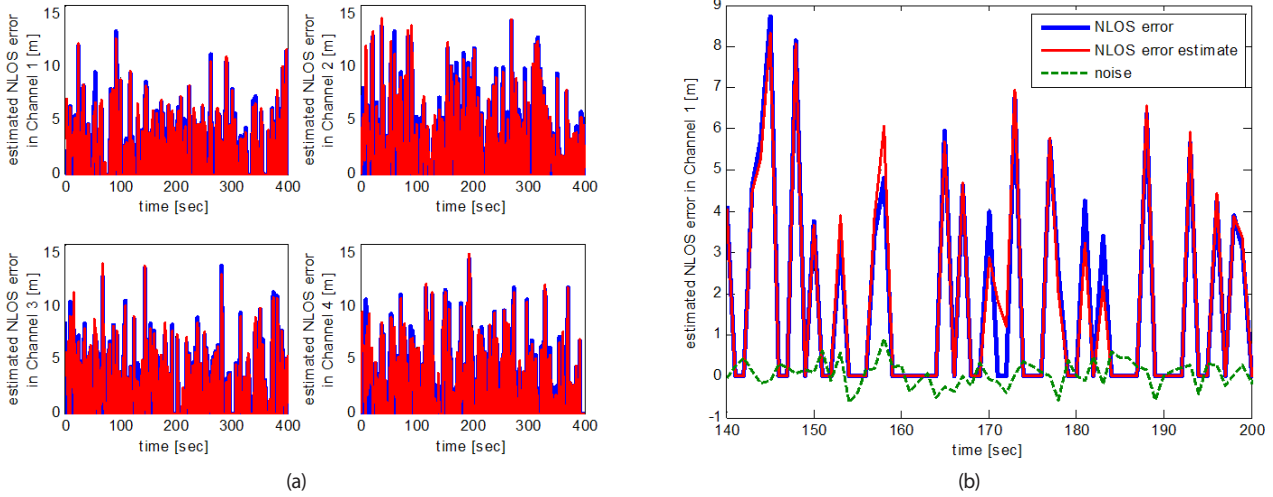


Fig. 4. Estimated channel-wise NLOS error in epoch-by-epoch localization. (a) channel-wise NLOS error and estimates (b) expanded figure.

two adaptive FbLMs estimate the more accurate location solutions than the EKF-based localization method. Also, Fig. 2c shows that the velocity estimate of the adaptive filter 2-based localization method is faster than the other methods in a situation where the velocity or moving direction of the MN changes quickly.

For convenient comparison, the errors of the instantaneous estimated locations are shown in Fig. 3, with the associated estimation results from ILS- and EKF-based localization methods. As shown in Fig. 3a the performance of the FbLMs is better than the FfLM. Moreover, the presented adaptive FbLMs has enhanced performance as contrasted with the EKF-based localization method. For analyzing the localization accuracy from different localization methods, the Root Mean Square Error (RMSE) of 1,000 localization solutions is used.

$$RMSE_k = \sqrt{\frac{1}{1,000} \sum_{i=1}^{1,000} ((x_k^m - \hat{x}_k^m(i))^2 + (y_k^m - \hat{y}_k^m(i))^2)} \quad (21)$$

Fig. 3b shows the RMSEs for the ILS-, EKF-, adaptive filter 1- and adaptive filter 2-based localization methods. This figure gives the comparison with the ILS- and EKF-based localization methods. The presented methods are significantly more accurate within the context of this simulation. Fig. 3c shows the RMSEs in the situation where the NLOS error absents. When the MN moves with constant velocity, the RMSEs of the location estimates from the FbLMs are smaller than the ILS. Also, the performance among the FbLMs may seem similar. The peaks of the FbLMs are near corners of the trajectory from Fig. 2a. This phenomenon is caused by the single model-based filtering. To reduce this error factor, the process noise covariance matrix is tuned in the adaptive filter 2. It can be seen that

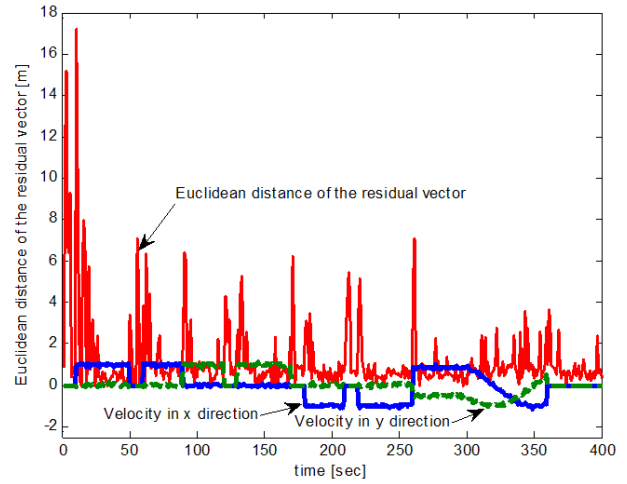


Fig. 5. EDRV after mitigating the NLOS error and velocities in x- and y-directions.

the adaptive filter 2 can reduce the error factor slightly. However, the results show that the limit of the single model-based filtering, that is the peak errors cannot be eliminated in the single model-based filter.

In Fig. 4, the performance of the NLOS error estimation using the filter residual can be analyzed. Fig. 4a shows the channel-wise NLOS error and the estimates from the adaptive filter 1. For convenient analysis, the result figure for the channel 1 is expanded in Fig. 4b. As shown in this figure, the filter residual-based NLOS error estimates in epoch-by-epoch localization are so accurate in comparison with true NLOS error that the NLOS error can be compensated almost perfectly in the presence of noise. It is directly attributable to the results of the adaptive filter 1-based localization as shown in Figs. 2 and 3.

To verify the usefulness of the adaptive filter 2, the EDRV

Table 1. Average of the estimated location RMSE using different localization methods.

		Localization Method			
		ILS	EKF	Adaptive Filter 1	Adaptive Filter 2
with NLOS error	Location [m]	2.80469	1.88182	0.65822	0.42849
	Velocity [m/s]	-	0.44681	0.23686	0.21208
without NLOS error	Location [m]	0.30107	0.41284	0.34028	0.28843
	Velocity [m/s]	-	0.25127	0.19582	0.16959

of the adaptive filter 1 is analyzed in Fig. 5. On the whole, it can be seen that the EDRV over the constant velocity course is less than 1.0 and the EDRV after changing the velocity or moving direction is larger than 2.0. That is, the suitability of the constant velocity model for the current moving situation can be analyzed using the EDRV. Based on this, the threshold for changing the process error covariance matrix is set equal to 1.5 in this simulation.

Finally, the averages of the estimated location/velocity RMSE using different localization methods are calculated as denoted in Table 1. In circumstances where the NLOS error exists such as indoor or urban area, the EKF-based localization method can provide more accurate location solution than the model-free localization methods. However, the performance enhancement of the EKF-based localization method has limit due to the NLOS error. The presented adaptive FbLMs can overcome the limit by mitigating the NLOS error. The localization errors of the adaptive filter 1 and adaptive filter 2 are 34.97784% and 22.76997% of that of the EKF, respectively. In the situation where the NLOS error absents, the model-free localization methods can yield accurate solutions. However, the estimation errors of the single model-based localization methods may be increased as shown in Fig. 3. Fortunately, the adaptive filter 2 can provide comparatively accurate and stable solutions without reference to the NLOS error.

It can be noted that, a drawback of the presented adaptive filter is that a single model is used. In the applications to the pedestrian's localization, a more model, constant acceleration model, can be adapted. To utilize two models in a filter, an IMM filter-like adaptive filter or model selection algorithm must be used. Consequently, more enhanced localization methods can be expected based on the multiple models by considering the application targets.

5. CONCLUSIONS

In this paper, a novel NLOS error mitigation method based on the filter with a single constant velocity dynamic model and range measurement was developed. It was revealed that the residual of the localization filter contains the NLOS error and the absolute value of the residual in

epoch-by-epoch localization can be accurate estimate of the NLOS error. By subtracting the NLOS error estimate from the range measurement, the accuracy of localization is improved. This method does not rely on the NLOS error scattering models. However, the single dynamic model-based filter causes time-delay estimation error when the speed or moving direction of a target mobile node changes rapidly. To reduce this error, a process noise covariance matrix tuning method is presented based on the residual of the NLOS error mitigated filter. The proposed methods, although they are very simple, provide a good performance by comparing with the conventional localization methods – iterative least squares- and extended Kalman filter-based localization methods. It can be expected that the proposed methods is well utilized to various applications of accurate wireless localization in NLOS error situations.

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