The Tracking Algorithm for Maneuvering Target Based on Adaptive Kalman Filter

Zheng Tang, Chao Sun, and Zongwei Liu
School of Marine Technology, Northwestern Polytechnical University, China

Abstract: *The application of kalman filter in tracking the maneuver target is not available as it is used in tracking the target of uniform motion. Therefore, a improved method for tracking a maneuver target is proposed. In the proposed approach, the maneuver detector provides the estimate of time instant at which a target starts to maneuver, when a target maneuver is determined, the kalman filter model will be adjusted with varied target motion state. The maneuver, modeled as an acceleration, is estimated recurslvely. Finally, the performance of the proposed approach is shown to be superior to kalman filter by simulation.*

Keywords: *Adaptive kalman filter, maneuver target tracking, maneuver detector, state estimation.*

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1. Introduction

The target tracking has been widely applied in military and civil. Many target tracking algorithms are proposed based on so many researches, such as alpha-beta filter, Gaussian sum filter and kalman filter and so on. Although it is convenient for computing, the alpha-beta filter is imprecision [18, 19]; Likewise, the Gaussian sum filter is precision, but it is complex to compute [14, 20]; The kalman filter is used for state estimation with linear dynamic system [2, 3, 9, 13], which can estimate the future state of signal based on the signal statistical characteristic. However, the well-known conventional kalman filter requires an accurate system model and exact prior information, which can not be directly used to track maneuver target.

For solving the problem, several researchers improved the existing methods. In [15], proposes an adaptive two-stage extended kalman filter using an adaptive fading EKF, and applies it to the inertial navigation system-global positioning system loosely coupled system with an unknown fault bias for estimating the unknown bias effectively although the information about the random bias was unknown. In [1] proposes the sensor information fusion kalman filter based on the introduced statistics of mathematical expectation of the spectral norm of a normalized innovation matrix. The approach allows for simultaneous test of the mathematical expectation and the variance of innovation sequence in real time and does not require a priori information on values of the change in its statistical characteristics under faults. In [4] extend the cubature kalman filter to deal with nonlinear state-space models of the continuous-discrete kind, and use the Itô-Taylor expansion of order 1.5 to transform the process equation, modeled in the form of stochastic ordinary differential equations, into a set of stochastic difference equations. In [16], proposes the relaying kalman filter algorithm which introduce the equations of updating sensor probability, and reconstruct the innovation equation.

But the more errors result from variations of the target motion state in maneuvering, which may seriously degrade the performance of the kalman filter or even cause the filter to diverge. Therefore, a novel approach based on adaptive variable kalman filter structure is proposed, which can adjust kalman filter model to the changes of target motion state in maneuvering. The maneuver detector is designed to determine that a maneuver is indeed occurring. Once a maneuver is detected a different state model is used by the filter: new state components are added. The extent of the maneuver as detected is then used to yield an estimate for the extra state components, and corrections are made on the other state components. The tracking is then done with the augmented state model until it will be reverted to the normal model by another decision. The rationale for using a lower order quiescent model and a higher order maneuvering model is the following: this will allow good tracking performance in both situations rather than a compromise.

The two models used here, described in section 2, are a constant velocity model for the quiescent situation and a constant acceleration model for the maneuvering situation. Section 3 describes how to determine that a maneuver is indeed occurring, and adjust motion state model. Finally, the simulation results are presented in section 4. An example has been simulated with the new algorithm as well with the input estimation algorithm. The results of Monte-Carlo runs of the two algorithms on the same system with the same random disturbances are presented. A unique feature of this work is that a rigorous statistical procedure is used to compare the two algorithms. The new algorithm is shown to be superior to the kalman filter for the example considered with high statistical significance. It consists not only of comparison of sample averages, as done usually in the literature, but a detailed analysis of differences. This methodology should have a wide applicability for comparison of algorithms in stochastic environments in a variety of problems.

2. The Problem Description

In tracking algorithm of maneuvering target, each model corresponds to each motion state, so the target motion model has to be established before research on the target tracking algorithms.

2.1. Non-Maneuvering Model

When the target moves at an even speed, the target motion state is only affected by the position and the velocity of the target, which is described as:

$$X(k+1) = \Phi X(k) + GW(k) \tag{1}$$

where, $X(k)$ is the state matrix of signal at time k, namely $X(k)=[x(k), V_x(k), y(k), V_y(k)]^T$; Φ is the state transition matrix; G is the input matrix; $W(k)$ is the state noise at time k, which is the zero-mean white Gaussian noise vector of variance Q caused by disturbances and modeling errors. The measurement model of sensor is given by:

$$Z(k+1) = H\,X(k) + V(k) \tag{2}$$

where, $Z(k)$ is the measurement vector at time k; H is observation matrix, namely $H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$; $V(k)$ is the measurement noise, which is the zero-mean white Gaussian noise vector of variance R caused by disturbances and modeling errors.

2.2. Maneuvering Model

When the target moves at an even acceleration, the target motion state will varies, which has to account for the variation of acceleration and is given by:

$$X^m(k+1) = \Phi^m X^m(k) + G^m W^m(k) \tag{3}$$

where, $X^m(k)$ is the state matrix of signal at time k, namely $X^m(k)=[x(k), V_x(k), y(k), V_y(k), a_x(k), a_y(k)]^T$; Φ^m is the state transition matrix; G^m is the input matrix; $W^m(k)$ is the state noise at time k, which is the zero-mean white Gaussian noise vector of variance Q^m caused by disturbances and modeling errors. In order to account for the variation of acceleration in time, components of the process noise enter the extra states in the maneuvering model. Simultaneously, the measurement model of sensor is changed by:

$$Z^m(k) = H^m X^m(k) + V^m(k) \tag{4}$$

where, $Z^m(k)$ is the measurement vector at time k; H^m is observation matrix, namely $H^m = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$; $V^m(k)$ is the measurement noise, which is the zero-mean white Gaussian noise vector of variance R^m caused by disturbances and modeling errors.

3. The Algorithm Description

The target maneuvers results in the filter gain reduces, so the non-maneuvering kalman filter model is not available as it is used in tracking the target of uniform motion [8, 11]. The maneuvering filter is sensitive to measurement noises and disturbances, and adjust motion model with maneuvering. However, the maneuvering filter often shows a bias in its velocity and position estimate, due to the fact that the filter cannot adjust its acceleration estimate as fast as the maneuver transition, especially if the filtering gain is small at the instant of maneuver termination [5, 10].

Therefore, in the design processes, it is important to establish the appropriate tracking model according to the target motion state. But due to lack of understanding of maneuvering degree and start time, it is difficult to establish the filter tracking model [12]. In order to solve the problem, the maneuvering detector is designed to apperceive the target motion state, if the target maneuvers, the motion state model is adjusted.

3.1. Estimation of The Target Maneuver

Besides the use of measurement concatenation, the proposed adaptive kalman filter method has consistent Decision Logic Window (DLW) for maneuver detection and estimation and effective reinitialization procedures for filter adaptation. A typical sequencing of operations of the DLW structure is depicted in Figure 1. The DLW operation procedure is described as follows. Start with the NMF. Monitoring and processing its innovations sequence may signal the occurrence of a maneuver. The detection of any abnormality in the innovations by the first decision logic triggers the MF with an appropriate initialization. At the same time, a second decision logic is activated, and used to verify the first decision by comparing the NMF and MF which are now operating in parallel. If it is a true maneuver, since the MF performs much better than the NMF during a maneuvering, the NMF will be stopped and the target state estimates switch from the NMF to the MF as the second decision is made. Otherwise, the first detection is denied. When the MF is in operation by itself, a similar decision procedure is applied to its innovations in order to determine the maneuver termination.

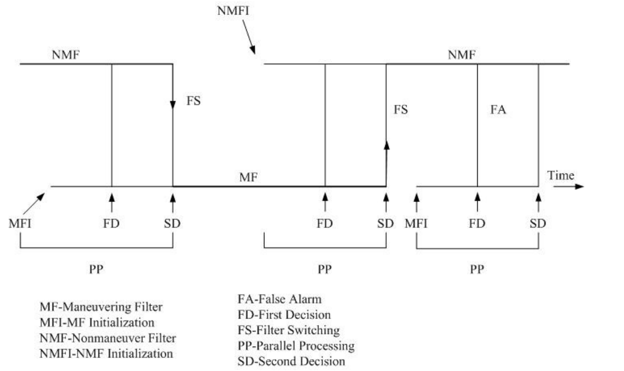

Figure 1. The sequencing of operations of the DLW structure.

For determining that a maneuver is indeed occurring, the proposed approach uses, at the present time k, the estimated input $\mu(k)$, its covariance $L(k)$ and the statistics $\zeta(k)$ for k-ξ+1, where ξ is the length of a fixed-size window, which are $\xi=(1-\gamma)^{-1}$. With the statistics, the maneuver detection can be performed in various ways. From the fact that the statistics $\zeta(k)$, is chi-square distributed with degrees-of-freedom under the assumption of zero input, we can choose the threshold η that satisfies the following equation with the probability of false alarm α:

$$P\{\zeta(k)\geq\eta\}=\alpha \tag{5}$$

With this value of η, the maneuver detection at time k is performed through the test:

$$\max\{\zeta(k), from\ k-\xi\ to\ k-1\}\geq\eta \tag{6}$$

If the target maneuver is detected, then the target maneuver onset time is also estimated using the statistics within the window in various ways. Hence, the following estimate t^* of the maneuver onset time is given in [7, 17]:

$$t^*=arg\ max\ \{\zeta(k), from\ k-\xi\ to\ k-1\} \tag{7}$$

Therefore, in a constant velocity model, this correspondence between estimates of the acceleration input suggests that the criterion equation 7 is equivalent to choosing at time k the kalman filter with a maximum a posteriori probability among ξ kalman filters for the constant velocity model conditioned upon that the target starts to maneuver at time from k-ξ to k-1.

While the variable dimension filter reestimates the states within the effective window for the augmented filter upon maneuver detection, the proposed filter changes to the maneuvering model without this laborious process. However in general, there is a tendency that the larger the maneuvering input is, the closer the estimated maneuver onset time approaches the time instant of declaring a maneuver detection, when a maneuver is detected. In this situation, insufficient data are used in estimating the unknown input and hence the confidence of the estimated input degrades. To resolve this unreliable situation, the proposed filter defines the minimum window length ξ_{min}, which is less than the effective window length. If the estimated starting time of the maneuver lies inside the minimum window, then the tracking system postpones changing to the maneuvering model. In other words, the tracking is carried out with the non-maneuvering model until the estimated maneuver onset time lies outside the minimum window, and the target model is changed to the augmented maneuvering model when this condition is satisfied. Since the maneuver detection is carried out by the significance test from the measurement sequences, the proposed scheme may increase the peak estimation error for rapid maneuvering target when changing to the maneuvering model.

When a maneuver is detected with the estimated maneuver onset time t^*, the state estimate of the augmented maneuvering model is initialized. The estimate of the state associated with target position and velocity, which is described as equation 1. Thereinto, $\Phi=\begin{bmatrix}1 & T & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & T\\ 0 & 0 & 0 & 1\end{bmatrix}$ and $G=\begin{bmatrix}T/2 & 0\\ 1 & 0\\ 0 & T/2\\ 0 & 1\end{bmatrix}$ in [6].

Assuming that the estimated starting time t^* of the maneuver is equal to the actual time instant t at which a target starts to maneuver, so the estimate of the state associated with the target acceleration, and its covariance, which is described as equation 3. Thereinto, $\Phi^m=\begin{bmatrix}1 & T & 0 & 0 & T^2/2 & 0\\ 0 & 1 & 0 & 0 & T & 0\\ 0 & 0 & 1 & T & 0 & T^2/2\\ 0 & 0 & 0 & 1 & 0 & T\\ 0 & 0 & 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 0 & 0 & 1\end{bmatrix}$ and $G^m=\begin{bmatrix}T^2/4 & 0\\ T/2 & 0\\ 0 & T^2/4\\ 0 & T/2\\ 1 & 0\\ 0 & 1\end{bmatrix}$ in [19].

When the estimation input is less than the threshold T_a, the acceleration estimation is no significant, so the filter model quit from maneuvering model to non-maneuvering model.

3.2. Kalman Filter

When the filter model is determined by adjusting kalman filter model with varied target motion state, the target motion state can should be obtained by inference of the kalman filter. Therefore, in target tracking process, the motion track is regarded as a discrete dynamic system, so the filter process is described by:

1. The value of the prediction at k is:

$$\hat{X}(k\mid k-1)=\Phi(k,k-1)\hat{X}(k-1\mid k-1) \tag{8}$$

2. The value of the state filter is:

$$\hat{X}(k\mid k)=\hat{X}(k\mid k-1)+K(k)[Z(k)-H(k)X(k\mid k-1)] \tag{9}$$

3. The gain matrix:

$$K(k)=P(k\mid k-1)H^T(k)[H(k)P(k\mid k-1)H^T(k)+R(k)]^{-1} \tag{10}$$

4. The prediction error at k is:

$$P(k \mid k-1) = \Phi(k,k-1)P(k-1 \mid k-1)\Phi^T(k,k-1) + G(k-1)Q(k-1)G^T(k-1) \quad (11)$$

5. The filter mean error:

$$P(k \mid k) = [I - K(k)H(k)]P(k \mid k-1) \quad (12)$$

The kalman filter infer the current estimated value from the new data and previous estimated value based on the recurrence formula and state transition equation, which can reduce the computation for processing the non-stationary time-varying signal.

4. The Simulation Result

For validating the effect of maneuvering target tracking, the proposed method and the kalman filter method are used to track the same maneuvering target, which the result of tracking is compared.

It is supposed that the target moves line along negative direction of the x-axis at even speed from 0~400s, the velocity is -15m/s, the initial condition of the target is given by (2000m, 10000m). From 401~600s, the target make a turn 90° to the positive direction of the x-axis, the acceleration is $a_x=a_y=0.075\text{m/s}^2$, which reduces the zero at the end. From 620s, the target make a turn 90° to the positive direction of the y-axis, the acceleration is $a_x=-0.3\text{m/s}^2$ and $a_y=0.3\text{m/s}^2$, which reduces zero at 670s. And then, from 1000s the target make a turn 90° to the negative direction of the x-axis, the acceleration is $a_x=a_y=-0.075\text{m/s}^2$, which reduces the zero at the end. From 1205s, the target make a turn 90° to the negative direction of the y-axis, the acceleration is $a_x=a_y=-0.3\text{m/s}^2$, which reduces zero at 1255s. Then, from 1455s the target make a turn 90° to the positive direction of the x-axis, the acceleration is $a_x=a_y=0.075\text{m/s}^2$, which reduces the zero at the end. The target over the motion at 1700s, and the target track is shown as Figure 2.

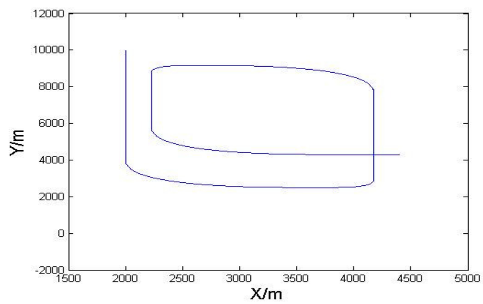

Figure 2. The real track of the target.

It is supposed that the scan period of the sensor is T=1s, the errors of the measurement are the 100m. In the start of the tracking, the filter model adopts the non-maneuvering model, from the start of the twentieth samples, the maneuvering detector is activated. For reflecting the filter effect really, the Monte-Carlo method is used to compute the mean and covariance by statistical analysis.

$$\bar{e}_x(k) = \frac{1}{M}\sum_{i=1}^{M}[x_i(k) - \hat{x}_i(k \mid k)] \quad (13)$$

$$\sigma_x = \sqrt{\frac{1}{M}\sum_{i=1}^{M}[x_i(k) - \hat{x}_i(k \mid k)]^2 - \bar{e}_x^{\,2}(k)} \quad (14)$$

where, M is the simulation times of the Monte-Carlo, k is the sample times. More the simulation times is, the result of the simulation is more approach the reality. The M=50 in the simulation.

4.1. The First Simulation

The simulation result through the 50 times Monte-Carlo simulation with kalman filter is shown as the Figure 3, the mean and the covariance of the x-axis and y-axis are shown as the Figure 4.

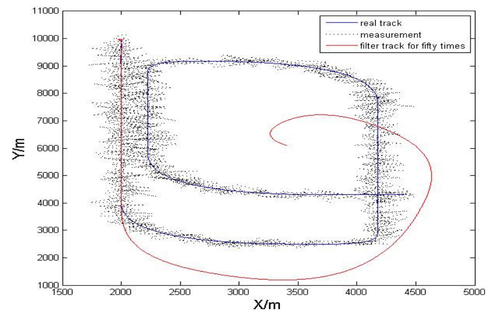

Figure 3. The tracking result of the kalman filter for fifty times Monte-Carlo.

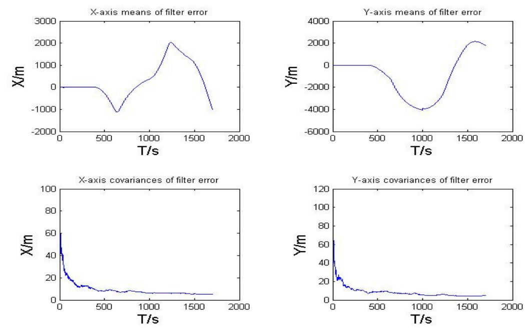

Figure 4. the mean and the covariance of the x-axis and y-axis.

From the Figures 3 and 4, we can see that the tracking result is precise in previous 400s, because of the uniform linear motion of the target. But the maneuvering target seriously degrades the performance of the kalman filter or even causes the more errors.

4.2. The Second Simulation

Firstly, it is supposed that the weighted attenuation gene is γ=0.8, the threshold of the maneuvering detector is η=35, and the threshold of the exit is T_a=9.49. The simulation result through the 50 times Monte-Carlo simulation with proposed method is shown as the Figure 5, the mean and covariance of the x-axis and y-axis are shown as the Figure 6.

From the Figures 5 and 6, we can see that the proposed method can improve the tracking precision evidently. Although the errors is still more when the target starts to maneuver, it is more less than the result of the Figures 3 and 4. Moreover, the threshold of the maneuvering detector affects tracking precision, the filter result, the mean and covariance of the threshold of the maneuvering detector η=20 are shown as the Figures 7 and 8.

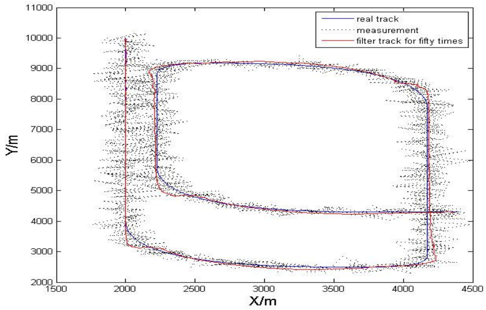

Figure 5. The tracking result of the proposed method by when η=35.

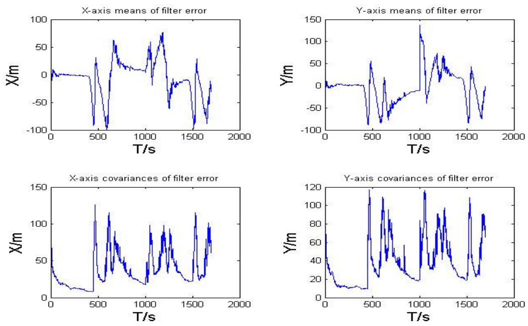

Figure 6. The mean and covariance of the x-axis and y-axis when η=35.

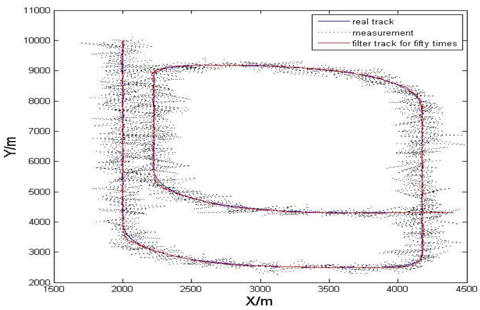

Figure 7. The tracking result of the proposed method by when η=20.

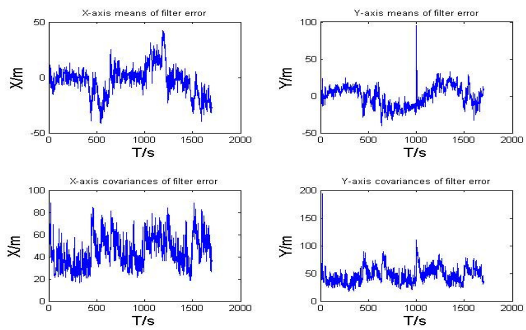

Figure 8. The mean and covariance of the x-axis and y-axis when η=20.

From the Figures 7 and 8, we can see that the tracking precision is improved greatly, especially at the turning, the tracking precision is better than results of the Figures 5 and 6. So the filter effect relates to the threshold of the maneuvering detector, and the performance of the tracking should be improved by adjust the threshold.

Overall, the proposed filter shows favorable tracking performance compared with that of the kalman filter. Furthermore, the proposed filter is adaptable to various maneuvering without any modification.

4.3. The Third Simulation

For verify the proposed algorithm can well performs with a target that is both changing direction and velocity. It is supposed that the target moves line along negative direction of the x-axis at even speed from 0~400s, the velocity in the direction of the y-axis is -15m/s, and the velocity in the direction of the x-axis is 2m/s. From 401~600s, the target maneuver, the acceleration in the direction of the y-axis is 0.175 m/s^2, and the acceleration in the direction of the x-axis is 0.075 m/s^2. The target track is shown as Figure 9.

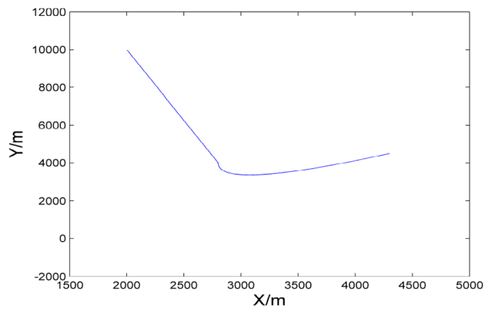

Figure 9. The real track of the target.

The simulation result through the 50 times Monte-Carlo simulation with kalman filter and the proposed method are respectively shown as Figures 10 and 11, the mean and the covariance of the x-axis and y-axis are respectively shown as Figures 12 and 13. Moreover, it is supposed that the weighted attenuation gene is γ=0.8, the threshold of the maneuvering detector is η=20, and the threshold of the exit is T_a=9.49.

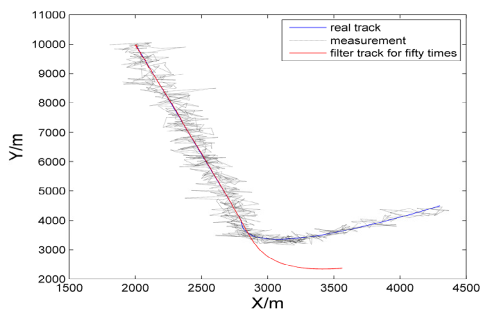

Figure 10. The tracking result of the kalman filter for fifty times Monte-Carlo.

From the Figures 11 and 13, we can see that the tracking precision is improved greatly, especially at the turning, the tracking precision is better than results of the Figures 10 and 12. These are all enough to justify the claims that this algorithm is categorically better than the straight kalman filter.

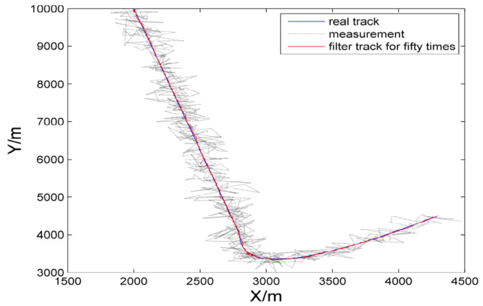

Figure 11. The tracking result of the proposed method by when η=20.

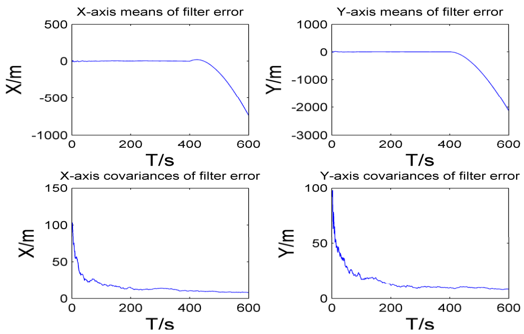

Figure 12. The mean and the covariance of the x-axis and y-axis obtained by the kalman filter.

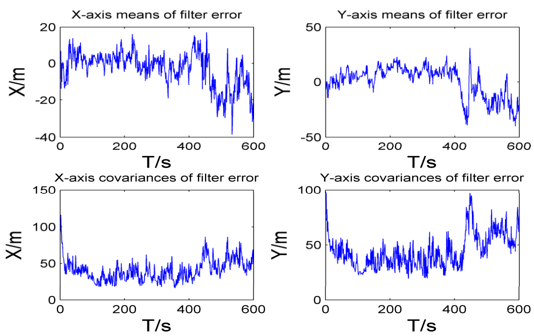

Figure 13. The mean and the covariance of the x-axis and y-axis obtained by the proposed method.

5. Conclusions

Compared with the kalman filter, the proposed adaptive filter model can adjust the order of kalman filter according to the threshold of maneuvering detector. The detector requires a minimum amount of computation and memory. The filter remains in its normal mode for most of the time and goes to the augmented model only when it detects that maneuvering has taken place. Therefore, the proposed filter behaves more adaptively by actively estimating the starting time of the maneuver. Also, the proposed filter resolves the computational problem which arises during the initialization process in the adaptive kalman filter. Computer simulation results demonstrate the effectiveness of the proposed filter in tracking a maneuvering target. Since the required statistics within the effective window are computed recursively, the proposed filter requires no more computational load than that of the kalman filter. Moreover, In application, the target motion state model is choose based on the maneuvering performance, which can increase the scope of application of the algorithm.

References

[1] Ali O., Chingiz H., and Ulviyye H., "Fault Detection in Sensor Information Fusion Kalman Filter," *International Journal of Electronics and Communications*, vol. 63, no. 3, pp. 762-768, 2009.

[2] Al-Najdawi N., Tedmori S., Edirisinghe E., and Bez H., "An Automated Real-Time People Tracking System Based on KLT Features Detection," *International Arab Journal of Information Technology*, vol. 9, no. 1, pp. 100-107, 2012.

[3] Anderson J., "An Ensemble Adjustment Kalman Filter for Data Assimilation," *Monthly Weather Review*, vol. 129, no. 12, pp. 2884-2903, 2001.

[4] Arasaratnam I., Haykin S., and Hurd T., "Cubature Kalman Filtering for Continuous Discrete Systems: Theory and Simulations," *IEEE Transaction on Signal Processing*, vol. 58, no. 10, pp. 4977-4993, 2010.

[5] Arrospide J., Salgado L., and Nieto M., "Multiple Object Tracking using an Automatic Variable Dimension Particle Filter," *in Proceedings of IEEE 17th International Conference on Image Processing*, Hong Kong, pp. 49-52, 2010.

[6] Bar-Shalom Y. and Birmiwal K., "Variable-Dimensional Filter for Maneuvering Target Tracking," *IEEE Transactions on Aerospace and Electronic System*, vol. 18, no. 5, pp. 621-629, 1982.

[7] Bogler P., "Tracking a Maneuvering Target using Input Estimation," *IEEE Transactions on Aerospace and Electronic System*, vol. 23, no. 3, pp. 298-310, 1987.

[8] Cloutier J., Lin C., and Yang C., "Enhanced Variable Dimension Filter for Maneuvering Target Tracking," *IEEE Transactions on Aerospace and Electronic System*, vol. 29, no. 3, pp. 786-797, 1993.

[9] Dang V., "An Adaptive Kalman Filter for Radar Tracking Application," *in Proceedings of the Microwaves, Radar and Remote Sensing*, Ukraine, pp. 261-264, 2008.

[10] Duh F. and Lin C., "Tracking a Maneuvering Target using Neural Fuzzy Network," *IEEE Transaction on Systems, man, and Cybernetics-Part B: Cybernetics*, vol. 34, no. 1, pp. 16-33, 2004.

[11] Gilholm K. and Everett N., "A Novel Algorithm for Tracking Targets using Manoeuver Models," *in Proceedings of IET Seminar on Target Tracking and Data Fusion: Algorithms and Applications*, UK, pp. 141-146, 2008.

[12] Godsill S., Vermaak J., Ng W., and Li J., "Models and Algorithms for Tracking of Maneuvering Objects using Variable Rate Particle Filters," *in Proceedings of the IEEE*, pp. 925-952, 2007.

[13] He C., Quijano J., and Zurk L., "Enhanced Kalman Filter Algorithm using the Invariance Principle," *IEEE Journal of Oceanic Engineering*, vol. 34, no. 4, pp. 575-585, 2009.

[14] Horwood J. and Poore A., "Adaptive Gaussian Sum Filters for Space Surveillance," *IEEE Transaction on Automatic Control*, vol. 56, no. 8, pp. 1-13, 2011.

[15] Kim K., Lee J., and Park C., "Adaptive Two-Stage Extended Kalman Filter for a Fault-Tolerant INS-GPS Loosely Coupled System," *IEEE Transaction on Aerospace and Electronics Systems*, vol. 45, no. 1, pp. 125-137, 2009.

[16] Liu Z., Wang J., and Qu W., "Relaying Kalman Filters for Sensor Networks," *in Proceedings of the International Conference on Computer Design and Applications*, Qinhuangdao, pp. 618-621, 2010.

[17] Park Y., Seo J., and Lee J., "Tracking using the Variable Dimension Filter with Input Estimation," *IEEE Transactions on Aerospace and Electronic System*, vol. 31, no. 1, pp. 399-408, 1995.

[18] Rogers S., "Alpha-Beta Filter with Correlated Measurement Noise," *IEEE Transaction on Aerospace and Electronic Systems*, vol. 23, no. 4, pp. 592-594, 1987.

[19] Sharma S., Deshpande S., and Sivalingam K., "Alpha-Beta Filter Based Target Tracking in Clustered Wireless Sensor Networks," *in Proceedings of the International Conference on Communication Systems and Networks*, pp. 1-4, Bangalore ,2011.

[20] Tam W., Plataniotis K., and Hatzinakos D., "An Adaptive Gaussian Sum Algorithm for Radar Tracking," *Signal Processing*, vol. 77, no. 1, pp. 85-104, 1999.

Zheng Tang is a postdoctoral in Institute of Acoustical Engineering of Northwestern Polytechnical University. He received his BS degree in electrical engineering, the MS and PhD degrees in system engineering from Northwestern Polytechnical University, Xi'an, Shaanxi, China in 2003, 2006 and 2009 respectively. Now, His research interests include signal processing, informaiton fusion and artificial intelligence.

Chao Sun is a professor in signal and information processing. She received her BS degree in electrical engineering from Northwestern Polytechnical University, Xi'an, Shaanxi, P.R. China in 1986 and her PhD degree in electron and electric engineering from Loughborough University, UK in 1992. In the same year, she starts her research as a postdoctoral at Northwestern Polytechnical University. Her research interests include signal and information processing in sonar. From 2000 to 2001, she makes research in Scripps Institution of Oceanography as a high-grade visiting scholar. Since 2003, she has been a director in the Department of Acoustics and Information Engineering at Northwestern Polytechnical University, in the China Acoustics Acad., in the Shaanxi Acoustics Acad., and in the Current Acoustics Nationality Emphases Laboratory. She has obtained two items of national defence technology advancement third awards. She takes charge or takes part in many national emphases items.

Zongwei Liu is a candidate of doctor in the Department of Acoustic and Information Engineering of Northwestern Polytechnical University. He received his BS degree in electrical engineering from Northwestern Polytechnical University, Xi'an, Shaanxi, P.R. China in 2008. His research interests include acoustical signal proceeing and the underwater defense technology.