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이동표적을 위한 이동 창 함수 기반 추적 알고리즘

(Tracking Algorithm Based on Moving Slide Window for Manuevering Target)

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요 약

본 논문에서는 이동 창 함수 추적기라는 새로운 추적 알고리즘을 제안한다. 본 논문에서는 이동표적의 궤적을 효율적으로 추정하기 위해 과거 궤적의 정보를 포함하는 이동 구간이 선형이라는 가정을 한 선형 창 함수를 적용하여 구현한다. 제안된 알고리즘의 창 함수의 파라메터는 측정 잡음의 영향을 줄이기 위해 그리고 알파-베터 추적기와 비교하여 더 적은 계산량 증가로 빠른 이동 표적 추적을 구현하기 위해 적절하게 선택할 수 있다. 본 논문에서 제안한 창 함수 추적기를 검증하기 위해 잡음상황에서 선형과 비선형 궤적에 대한 컴퓨터 모의실험을 수행했다. 또한 제안된 창 함수 추적기는 초기값에 대한 둔감한 특성과 예측할 수 없는 시변 측정 환경에서 창 함수 추적기를 사용할 경우 더 높은 자유도를 가짐을 보였다.

Abstract

In this paper, we propose a novel tracking algorithm called slide window tracker (SWT) suitable for maneuvering target. To efficiently estimate trajectory of moving target, we adopt a sliding piecewise linear window which includes past trace information. By adjusting the window parameters, the proposed algorithm is to reduce measurement noise and to track fast maneuvering target with little computational increment as compared to α-β tracker. Throughout the computer simulations, we verify outstanding tracking performance of the SWT algorithm in noisy linear and nonlinear trajectories. Also, we show that the SWT algorithm is not sensitive to initial model parameter selection, which gives large degree of freedom in applying the SWT algorithm to unknown time-varying measurement environments.

Keywords : Schur algorithm, Slide window tracker, α-β tracker, Maneuvering target

Ⅰ. Introduction

In general, tracking filters work remove and estimate the states of system dynamics. The well known α-β tracking filter[1~2] and Kalman filter[3] estimate position and velocity by using measurements of maneuvering targets.

The Kalman filter shows excellent tracking performance, when the target dynamics and statistical characteristics of measurement noise are available, which is difficult to obtain in advance[4]. The disadvantage of the Kalman filter is a large amount of computational cost.

The α-β tracker is more popular than the Kalman filter due to low computational cost and its simplicity. Because of simplicity, the tracking accuracy of the α-β tracker is not

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guaranteed and sometimes target is lost when the target trajectory is nonlinear in noisy environment[4]. Also, the performance of the α-β tracker heavily depends on suitable choice of α and β, which make it difficult to be used for maneuvering target with AWGN (Additive White Gaussian Noise)[5].

To cope with these problems, we propose the SWT algorithm as an extension of the α-β tracker, which utilizes the Gaussian mean of past trace information by adopting sliding linear window. The Gaussian mean[6] is known to be a method to improve the SNR (Signal to Noise Ratio). The proposed algorithm does not require prior statistical characteristics of target and demands low computational cost. By changing parameters of noise, target trajectory, and variables, we demonstrate that the proposed method is less sensitive to algorithm parameters than the α-β tracker parameters. In the paper, Section 2 describes the SWT algorithm. Validity of the proposed method is demonstrated in Section 3. Conclusions are made in Section 4.

Ⅱ. SWT algorithm

The SWT is designed by regarding the short time interval of target trajectory as piecewise linear as shown in Fig. 1, in which x(k) is a linearized trajectory in the linear window model of the moving target[7], M is a discrete linear window size, and D_k is the moving interval of a target in between k-1 and k.

To predict the target position at the time of N+1, we include past tract information in the model by setting the equal intervals, $D_{N-M} \cong \cdots \cong D_N \cong D_{N+1}$ and assuming $D_k = D + \varepsilon$, k = N-M, ⋯, N-1, where ε is a small Gaussian random variable with zero mean. Then, if ε is zero such as perfect linear model, we can predict target position x(N+1) by using $x_p(N+1) = x(N) + D$ as shown in Fig. 1. Here note that noise is always present in D_k. To reduce he Gaussian random error, we propose an equation to calculate the predicted interval D by linear combining the previous estimates[2,7] as follows:

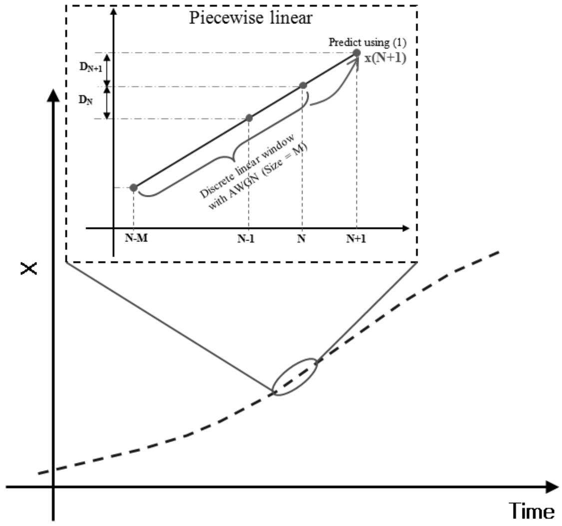

그림 1. 창 함수 추적기를 위한 선형 창 함수 개념
Fig. 1. Linear sliding widow logic for the SWT.

$$D \cong D_{N-M} + \frac{\mu}{M}\sum_{m=1}^{M}(D_{N-M+m} - D_{N-M}), \quad (1)$$

where μ is weight value.

Finally, using the predicted D in (1), the generalized equation of the predicted target position can be expressed as follows:

$$x_p(k+1) \cong x(k) + D, \quad (2)$$

where $x_p(k+1)$ is the predicted target position. The μ in (1) can be found by minimizing the mean-square error (MSE) cost function as follows:

$$E\{[x(k) - x_p(k)]^2\} = E\left\{\left[D - \mu D - \frac{\mu}{M}\sum_{m=1}^{M}\varepsilon_m\right]^2\right\}. \quad (3)$$

Assuming μ = 1 and M is a large, the left term of (2) approaches to a zero because ε has zero mean. To find filtered estimate, we use measurement update[1~2] as follows:

$$x(k) = x_p(k) + \alpha_s [x_m(k) - x_p(k)], \tag{4}$$

where x(k) and $x_m(k)$ denote filtered target position and measured target position at k, respectively, and α_s is a coefficient of the SWT. The α_s can be calculated from a relation of $E\{[x(k) - x_p(k)]^2\} = \alpha_s^2 E\{[x_m(k) - x_p(k)]^2\}$, with which we obtain the following:

$$\alpha_s = \frac{1}{\sqrt{1 + \frac{\sigma^2}{E\{[x(k) - x_p(k)]^2\}}}}, \tag{5}$$

where $x_m(k) = x(k) + \varepsilon_m$, $E\{\varepsilon_m\} = 0$, and $E\{\varepsilon_m^2\} = \sigma^2$. As the tracking process converges, the α_s becomes small because of $E\{[x(k) - x_p(k)]^2\}$.

For N iterations, the computations of the proposed algorithm are as 2N additions, N(M + 1) subtractions, and 3N multiplications. On the other hand, the α-β tracker needs 3N additions, 2N subtractions, and 4N multiplications. This implies that the computational cost of the proposed algorithm is compatible to the α-β tracker.

Ⅲ. Verifications

To verify the performance of the SWT, we compare the SWT with the α-β tracker. The coefficient α for the α-β tracker is obtained by the criterion based on the best linear track fitted to radar data in a least squares sense[8]. The coefficient β for the α-β tracker is 0.05 and the obtained value by the criterion based on the best linear track fitted to radar data in a least squares sense[4]. To verify the proposed algorithm, we assume target moves every 0.001 [sec] and stops at 25 [sec] and generate a slow and a fast varying target following equations

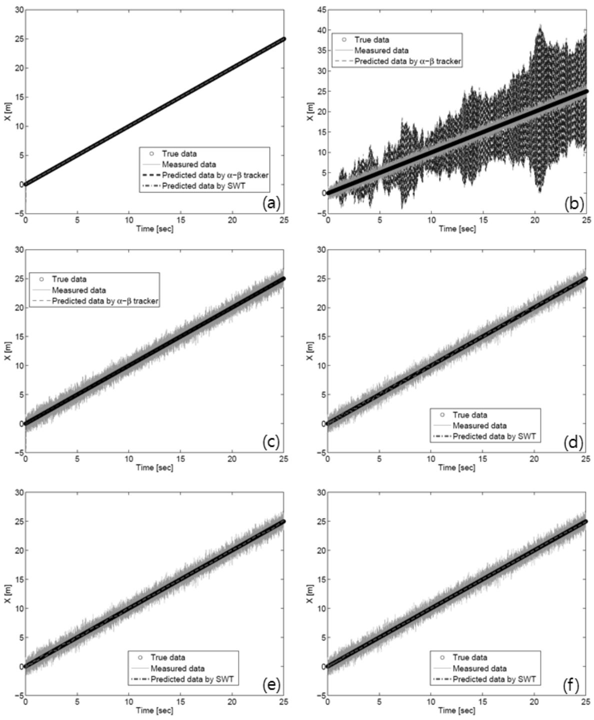

그림 2. 선형궤적을 위한 결과, (a) 잡음이 없는 경우 (창 함수 추적기와 알파-베타 추적기), (b) 잡음이 있는 경우 (알파-베타 추적기), (c) 잡음이 있는 경우 (알파-베타 추적기), (d) 잡음이 있는 경우 (창 함수 추적기), (e) 잡음이 있는 경우 (창 함수 추적기), (f) 잡음이 있는 경우 (창 함수 추적기)

Fig. 2. Results for linear trajectory, (a) without noise (both SWT and α-β tacker), (b) with noise (α-β tacker), (c) with noise (α-β tacker), (d) with noise (SWT), (e) with noise (SWT), (f) with noise (SWT).

of nonlinear trajectory $x_m(t) = 5\cos(2\pi t/30) + 1 + n(t)$, where noise n(t) is the Gaussian random noise with N~(0, 0.1) and linear trajectory $x_m(t) = t + n(t)$, where noise n(t) is N~(0, 0.5).

For initial parameters, we set arbitrary values of $x_p(1)$ and velocity V(1) for the α-β tracker and $x_p(1)$ and D for the SWT. In the paper, $x_p(1)$ = 1 [m] and V(1) = 0 [m/sec] are used. Note that the window size of the SWT is increased step by step from 1 to M. The error can be calculated as the square of the norm as $\| \underline{x_t} - \underline{x_p} \|^2$, where $\underline{x_t}$ and $\underline{x_p}$ are true data vector without noise and the prediction data vector, respectively.

Fig. 2 shows tracking performance of the SWT with the α-β tracker in linear trajectory when we set all $\alpha_s = \alpha = 2(2k+1)/k(k+1)$. In Fig. 2(a), when noise is not added, we can see that the errors of the two tracking algorithms are similar (errors are 1.99 for SWT (M = 5 and μ = 0.5) and 10.01 for α-β tracker (β = 0.05). Figs. 2(b) and 2(c) show the tracking of the trajectory with noise using the α-β tracker. The error is propagated in Fig. 2(b) for β = 0.05 (error is 1.09×10^{6}), and Fig. 2(c) for β = 6/k(k+1) shows a good result removing the error (error is 42.02), where k is a iteration number. Figs. 2(d), 2(e), and 2(f) show the tracking of the trajectory with noise using the SWT, and the algorithm is run changing M = 5, M = 25, and M = 100, respectively, we get better results than α-β tracker. The errors are 481. 81, 209.27, and 48.77, respectively, and we can see that a larger M is better for a linear trajectory.

Fig. 3 compares the SWT with the α-β tracker tracking a nonlinear trajectory, when we set all $\alpha_s = \alpha = 2(2k+1)/k(k+1)$. In Fig. 3(a), we can see that the errors of the two tracking algorithm for the trajectory without noise are similar (errors are 32.05 for SWT (M = 5 andμ = 0.5) and 16.98 for α-β tracker (β = 0.05). Figs. 3(b) and 3(c) show the tracking of the trajectory with noise using the α-β tracker. Fig. 3(b) for β = 0.05 is propagated the error (error is 1.1×10^{5}), and Fig. 3(c) for β = 6/k(k+1) is also propagated the estimation error of the nonlinear trajectory although noise are removed (error is 1.93×10^{5}). The results show that the set of α and β is important. Figs. 3(d), 3(e), and 3(f) show the tracking of the trajectory with noise using the SWT by changing M = 5, M = 25, and M = 100, respectively, we got that the α-β tracker is more sensitive than the SWT. The errors are 2.71×10^{2}, 62.12, and 1.58×10^{2}, respectively, and we can see that a optimum M exists.

In Fig. 4 we present sensitivity and convergence behavior of the SWT by changing the parameter (μ) in estimating noisy linear

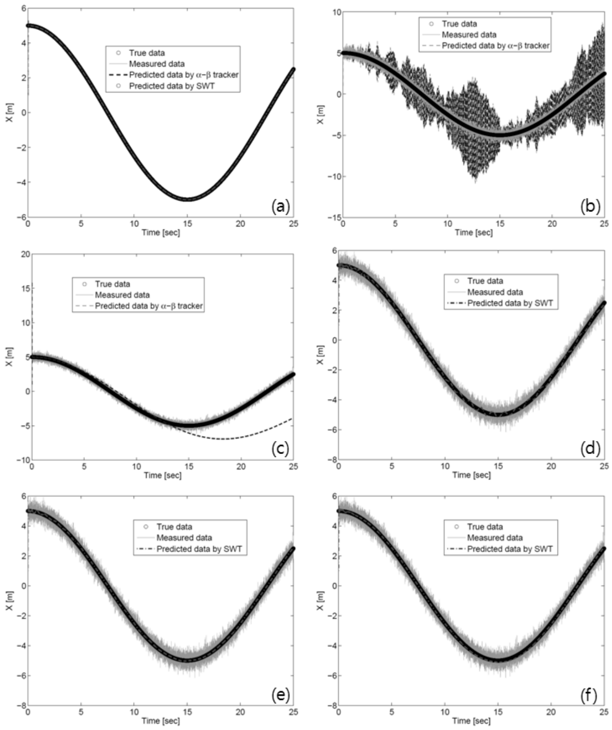

그림 3. 비선형궤적을 위한. 결과, (a) 잡음이 없는 경우 (창 함수 추적기와 알파-베타 추적기), (b) 잡음이 있는 경우 (알파-베타 추적기), (c) 잡음이 있는 경우 (알파-베타 추적기), (d) 잡음이 있는 경우 (창 함수 추적기), (e) 잡음이 있는 경우 (창 함수 추적기), (f) 잡음이 있는 경우 (창 함수 추적기)

Fig. 3. Results for nonlinear trajectory, (a) without noise (both SWT and α-β tracker), (b) with noise (α-β tracker), (c) with noise (α-β tracker), (d) with noise (SWT), (e) with noise (SWT), (f) with noise (SWT).

and nonlinear trajectories (the noise is the same that the cases of Figs. 2 and 3). Here, μ and β have changed as the every interval 0.005 in between 0 and 1, and we set as M=5, and $\alpha_s = \alpha = 2(k+1)/k(k+1)$. Figs. 4(a) and 4(c) show the errors an histogram of linear moving target. The errors and histogram of nonlinear moving target are depicted in Figs. 4(b) and 4(d). On the estimation error of both algorithms, their probability are less than 250 is almost the same as 0.21.

Next, we use α-β tracker and do the same simulations by using the same conditions used in Fig. 4. Figs. 5(a) and 5(c) show the errors and histogram of the linear moving target and the errors and their histogram of the nonlinear moving target are depicted in Figs. 5(b) and

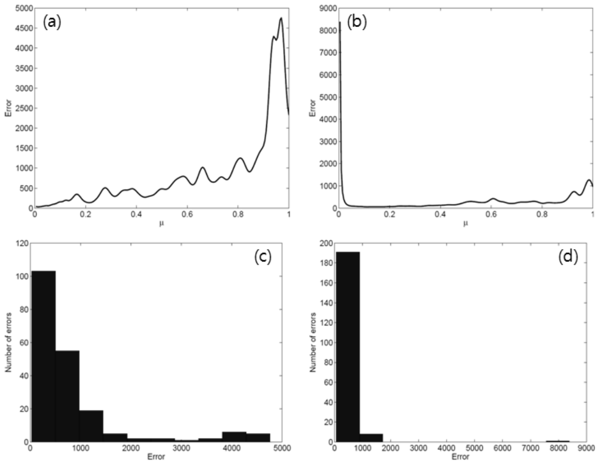

그림 4. 창 함수 추적기의 μ 변화에 대해 (a) 선형궤적과 (b) 비선형궤적 대한 에러와 (c) 선형궤적과 (d) 비선형궤적의 에러 히스토그램

Fig. 4. Errors for (a) linear trajectory and (b) nonlinear trajectory, and histogram (c) linear trajectory and (d) nonlinear trajectory along changing for μ the SWT.

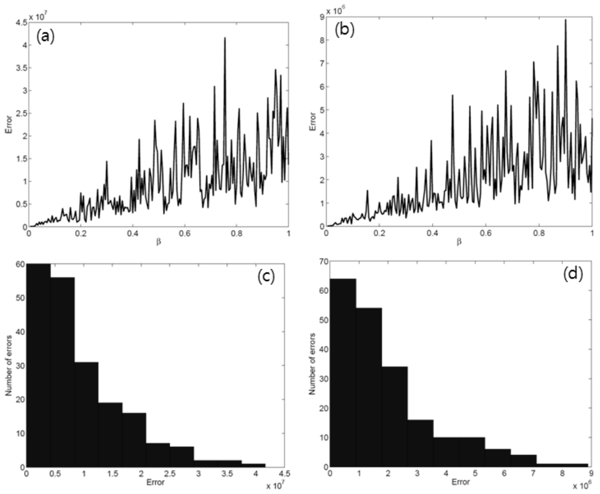

그림 5. 알파-베타 추적기의 β 변화에 대해 (a) 선형궤적과 (b) 비선형궤적 대한 에러와 (c) 선형궤적과 (d) 비선형궤적의 에러 히스토그램

Fig. 5. Errors for (a) linear trajectory and (b) nonlinear trajectory, and histogram for (c) linear trajectory and (d) nonlinear trajectory along changing β for the α-β tracker.

5(d). The probabilities of estimation errors are less than 250 are both 0.005. With these comparisons, we show that SWT is superior to α-β tracker.

In order to show the insensitivity to parameters of SWT, we have calculated the estimated errors by changing μ and M as shown in Fig.6. Here, μ have changed as the

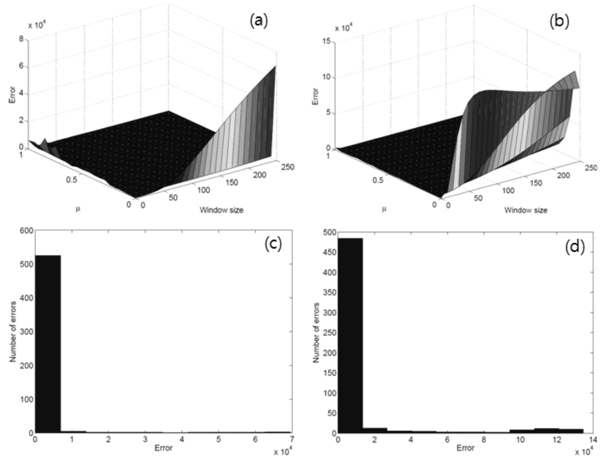

그림 6. 창 함수 추적기의 μ와 M 변화에 대해 (a) 선형궤적과 (b) 비선형궤적 대한 에러와 (c) 선형궤적과 (d) 비선형궤적의 에러 히스토그램

Fig. 6. Errors for (a) linear trajectory and (b) nonlinear trajectory, and histogram for (c) linear trajectory and (d) nonlinear trajectory along changing μ and M by the SWT.

every interval 0.05 from 0 to 1, M have changed as the every interval 10 in between 0 and 250, and α is set as $\alpha = 2(k+1)/k(k+1)$. Figs. 6(a) and 6(c) show the errors and histogram of the noisy linear moving target. The results of the nonlinear target are depicted in Figs. 6(b) and 6(d). The estimation error probabilities of each trajectory is less than 250, are 0.822 and 0.511, respectively. With these results, we can conclude that the SWT is not sensitive to parameter selection for both linear and nonlinear trajectories. Comparing two trajectories, the SWT is more sensitive to nonlinear than the linear. The proposed SWT algorithm can apply in tracking software for various radar and sonar systems[9~10].

Ⅳ. Conclusions

In the paper, we have proposed a novel tracking algorithm called slide window tracker suitable for fast maneuvering target in noisy channel. To efficiently estimate trajectory from noisy moving target measurement, we have utilized a sliding piecewise linear window including past trace information. By adjusting the window parameters, the proposed algorithm is to reduce measurement noise and to track fast maneuvering target. The computational increment of the proposed algorithm with comparison to α-β tracker is negligible. Throughout the computer simulations, we have demonstrated outstanding tracking performance of the SWT algorithm in severe noisy linear and nonlinear measurement. Also, we have presented that the SWT algorithm is not sensitive to initial model parameter selection. Thus, we can apply the SWT algorithm to tracking problem of unknown nonlinear time-varying measurements with large degree of freedom.

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