A Thesis for the Degree of

Master of Engineering

Statistical Signal Processing Algorithms for Radar and Sonar System

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GRADUATE SCHOOL
CHEJU NATIONAL UNIVERSITY

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SUMARY

The ocean equipments such as maritime radar and sonar system play a vital role in ship navigation, collision avoidance and ocean investigation. Especially such equipments require great accuracy and reliability. To improve the performance of those equipments, statistical signal processing methods will be required.

Typical maritime radar is used either in the α-β tracker or the Kalman tracker to track moving targets. However, if α and β coefficients are not suitable, the α-β tracker does not guarantee the accuracy of the position and velocity estimation for a non-linear moving target. The Kalman tracker demands the statistical characteristics of the maneuvering targets and it has a heavy computational cost. To solve the problems, the switched slide window tracker (SSWT) using a moving piecewise window was proposed in this study. The proposed algorithm does not require the statistical characteristics of a target and demands low computational cost. To verify the algorithm, the maritime radar simulator with the proposed algorithm is implemented using a TMS320C6711 digital signal processor (DSP) board and LabVIEW 8.5.

In the underwater communications, transmitted acoustic signal is corrupted by interference from multipath. A parametric array transducer is capable of radiating a narrow beam with very low sidelobe levels. In certain cases, the parametric array transducer can help the multipath

problem. In the thesis, the sonar communication system using the parametric array transducer was presented. To detect the signal without error, the measured signal was averaged for a particular window size before applying the maximum likelihood method.

Our implementation has the potential to improve the performance of the ocean equipments such as radar and sonar system.

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CHAPTER 1
Introduction

The ocean equipment such as maritime radar and sonar system play a vital role in ship navigation, collision avoidance, ocean investigation and underwater communication [1]. Especially these equipments require great accuracy and reliability [2]. To improve the performance of these equipments, the statistical signal processing method will be required [3].

Typical maritime radar is used either in the α-β tracker or the Kalman tracker to track moving targets [4]. However, if α and β coefficients are not suitable in the case of a non-linear moving target, the accuracy of the position and velocity estimation is not guaranteed [5]. The Kalman tracker demands the statistical characteristics of the maneuvering targets and it has a heavy computational cost [6]. To solve these problems, the switched slide window tracker (SSWT) using a moving piecewise window was proposed in this study [7]. The proposed algorithm does not require the statistical characteristics of a target and demands low computational cost. In addition, our algorithm is more effective than the α-β tracking tracker for a non-linear moving target. To verify the algorithm, the maritime radar simulator with the α-β tracker, the Kalman tracker and the proposed algorithm is implemented using a TMS320C6711 digital signal processor (DSP) board and LabVIEW 8.5 [8] [9].

In the underwater communications, transmitted acoustic signal is corrupted by interference from multipath [10]. A parametric array transducer is capable of radiating a narrow beam with very low sidelobe levels [11]. In certain cases, the parametric array transducer can help the multipath problem. In the thesis, the sonar communication system using the parametric array transducer was presented. To detect the signal without error, the measured signal was averaged for a particular window size before applying the maximum likelihood method [12]. The graphic user interface (GUI) control programs for the sonar communication system are developed by LabVIEW 8.5, which can be modified easily.

Chapter 2 presents the maritime radar simulator using the proposed tracking algorithm. Chapter 3 presents the parametric array sonar system using the prototype parametric array transducer. Finally, Chapter 4 describes some of the research results.

CHAPTER 2

The Maritime Radar Simulator

2.1 Introduction

Maritime radar and sonar system play a vital role in ship navigation, collision avoidance [1]. Typical maritime radar is a track while scan (TWS) radar, which is used either in the α-β tracker or the Kalman tracker to track moving targets [4].

In cases where the statistical characteristics of the maneuvering targets are known exactly, the Kalman tracker gives an excellent tracking performance [13]. However, it is difficult to find the statistical characteristics of the maneuvering target in advance. Furthermore, the Kalman tracker has a heavy computational cost [6].

The α-β tracker is more popular than the Kalman tracker because of its simplicity and it does not demand high computational cost [7]. However, if α and β coefficients for non-linear moving target are not suitable for a non-linear moving target, the accuracy of the position and velocity estimation is not guaranteed [5].

To solve these problems, the switched slide window tracking (SSWT) algorithm using a moving piecewise window was proposed in the thesis [7]. The proposed algorithm does not require prior statistical characteristics of a target and demands low computational cost. In addition, the proposed algorithm is more effective than the α-β tracking tracker for non-linear moving targets.

To verify the algorithm, the maritime radar simulator with the α-β tracker, the Kalman tracker and the SSWT is implemented using a TMS320C6711 digital signal processor (DSP) board [8] [9]. The simulator is used to track and display the moving target, and it has graphic user interface (GUI).

Section 2.2 gives a brief overview of the different algorithms used in the α-β tracker, the Kalman tracker and the proposed tracker. Section 2.3 presents the maritime radar simulator using the proposed algorithm. Finally, Section 2.4 describes some of the research results.

2.2 Conventional Algorithms

2.2.1 The α-β Tracker

The α-β tracker is used for tracking targets. The α-β tracker is defined as

$$\begin{aligned} & x_F(k) = x_p(k) + \alpha\left[x_m(k) - x_p(k)\right], \\ & V_F(k) = V_p(k) + \beta / T\left[x_m(k) - x_p(k)\right], \\ & x_p(k+1) = x_F(k) + V_F(k)T, \\ & V_p(k+1) = v_F(k), \end{aligned} \tag{2-1}$$

where $x_m(k)$ is the x coordinate of the target's measured position, $x_p(k)$ is the x coordinate of the target's predicted position, $V_p(k)$ is the predicted target velocity in the x direction, $x_F(k)$ is the x coordinate of the filtered target position, $V_F(k)$ is the filtered target velocity in the x direction at k_{th} scan, T is the radar scan time or the scanning period. α is the position smoothing parameter, and β is the velocity smoothing parameter. The α-β coefficients are related by [4]

$$\beta = \alpha^2 / (2 - \alpha) \tag{2-2}$$

Computer simulation was done to prove the performance of the proposed algorithm. The performance with the different coefficient α, β was compared in the simulation. The criterion for selecting the α-β coefficients is based on the best linear track fitted to radar data in a least squares sense. The α-β coefficients is given by [4]

$$\alpha = (2(2k-1))/(k(k+1)). \tag{2-3}$$

$$\beta = 6/(k(k+1)). \tag{2-4}$$

where k is the number of the scan or target observation (k>2).

In the simulation, the radar measures the positions of the moving target once per second, and 200 iterations was performed. Two target models, a linear moving target model and a non-linear moving target models are used in this simulation.

In the thesis, simulations with three moving target models were carried out. The moving target models are described in Table 2-1.

Table 2-1. The target model for the simulation

Target Model	**Equations**
Model I (a linear moving target model)	$x_m(t) = 10(t) + 10$ $y_m(t) = 10(t) + 10$
Model II (a non-linear moving target model)	$x_m(t) = 3\pi(t) + 15(t) - 10(t)^{1.2} + 100$ $y_m(t) = 150\sin(0.9\pi(t)/100) + 20$
Model III (a non-linear moving target model)	$x_m(t) = 0.1614t^3 - 0.9682t^2 + 7.8083t + 6$ $y_m(t) = 0.04t^2 + 0.4679\sin(t^2) + 4t + 5$

The error function is defined as

$$err = \sum_{i=1}^{N} \sqrt{(x_t(k) - x_p(k))^2 + (y_t(k) - y_p(k))^2} \tag{2-5}$$

where $x_t(k)$, $y_t(k)$ are the x, y coordinates of the target's true position, $x_p(k)$, $y_p(k)$ are the x, y coordinates of the target's predicted position.

Example I: Tracking a linear moving target model (Model I) using the α-β tracker

The α-β tracker is operated for the four different values of the coefficient α, 0.3, 0.7, 1 and the variable obtained from (2-3). In the simulation, Gaussian noise with a mean of zero that is distributed with a variance of 0.1 is used. The coefficient β is obtained from (2-4). Figure 2-1 illustrates the tracking when a target has a straight trajectory with constant velocity.

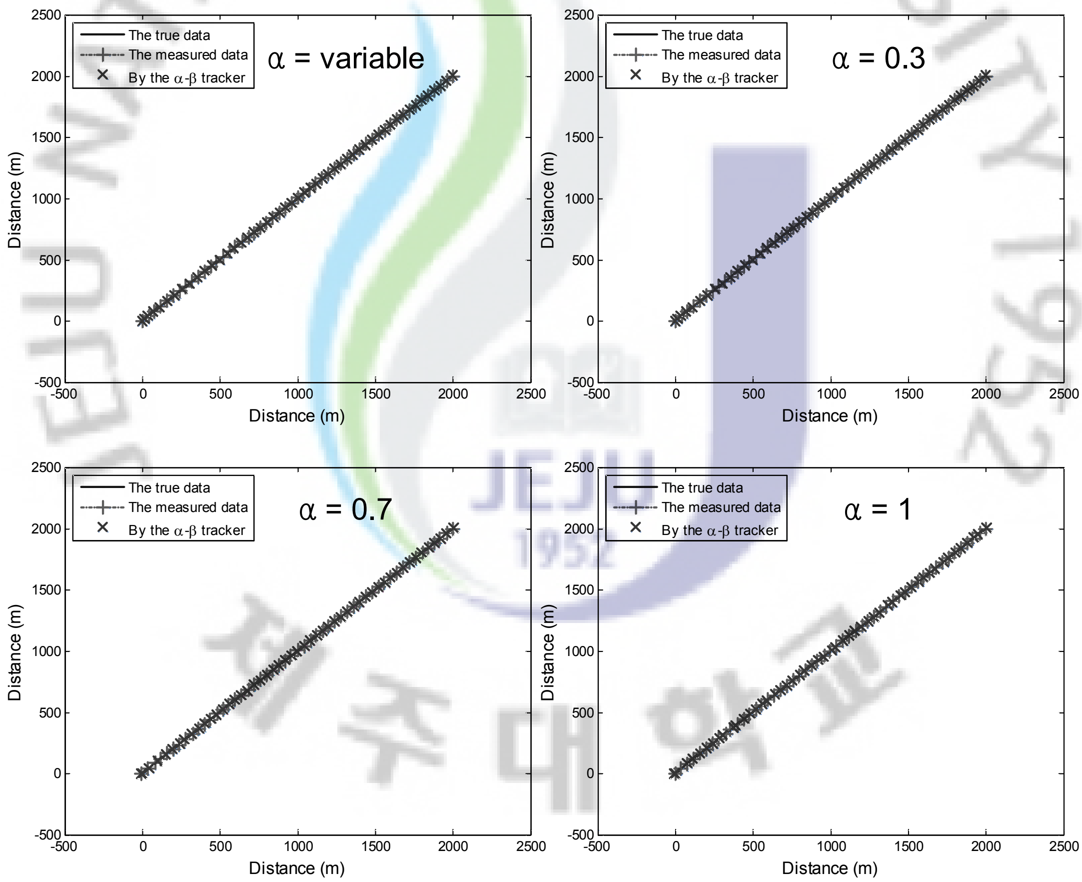

Figure 2-1. Attained simulation results of the α-β tracker

As shown in Fig. 2-1, the α-β tracker shows good tracking performance for a linear moving target model (Model I). Using (2-5), the errors are calculated for the four different values of the coefficient α, 0.3, 0.7, 1 and the variable from (2-3). Fig. 2-2 illustrate the error curves by the coefficient α.

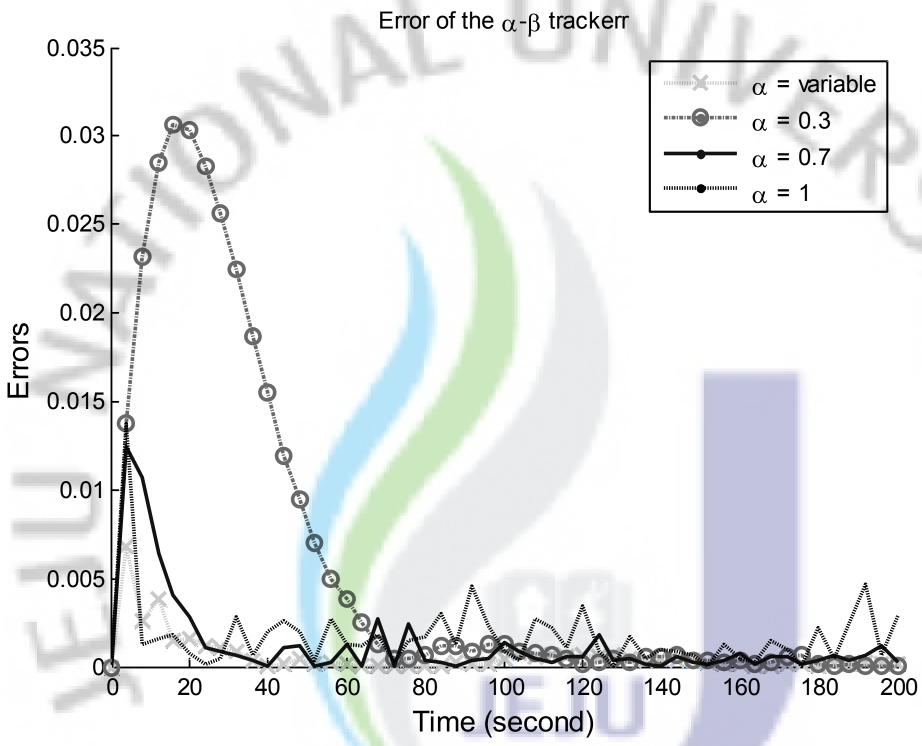

Figure 2-2. The error curves by the coefficient α

As shown in Fig. 2-2, the α-β tracker is not suitable for a linear moving target model (Model I) in case of a coefficient α is 0.3. The errors are given in Table 2-2.

Table 2-2. Error of the α-β tracker

α	variable	0.3	0.7	1
Error	112.2	1194.7	310.6	346.6

From the results, the α-β tracker shows the best tracking performance when the coefficient α is a variable. However, the coefficient α 0.3 is not suitable in case of the linear moving target model (Model I).

Example II: Tracking a non-linear moving target model (Model II) using the α-β tracker

The α-β tracker is operated for the four different values of the coefficient α, 0.3, 0.7, 1 and the variable obtained from (2-3). In the simulation, the Gaussian noise used is same as in ***Example I***. The coefficient β is obtained from (2-4). Fig. 2-3 illustrates the tracking when a target has a sharp turn trajectory with variable velocity.

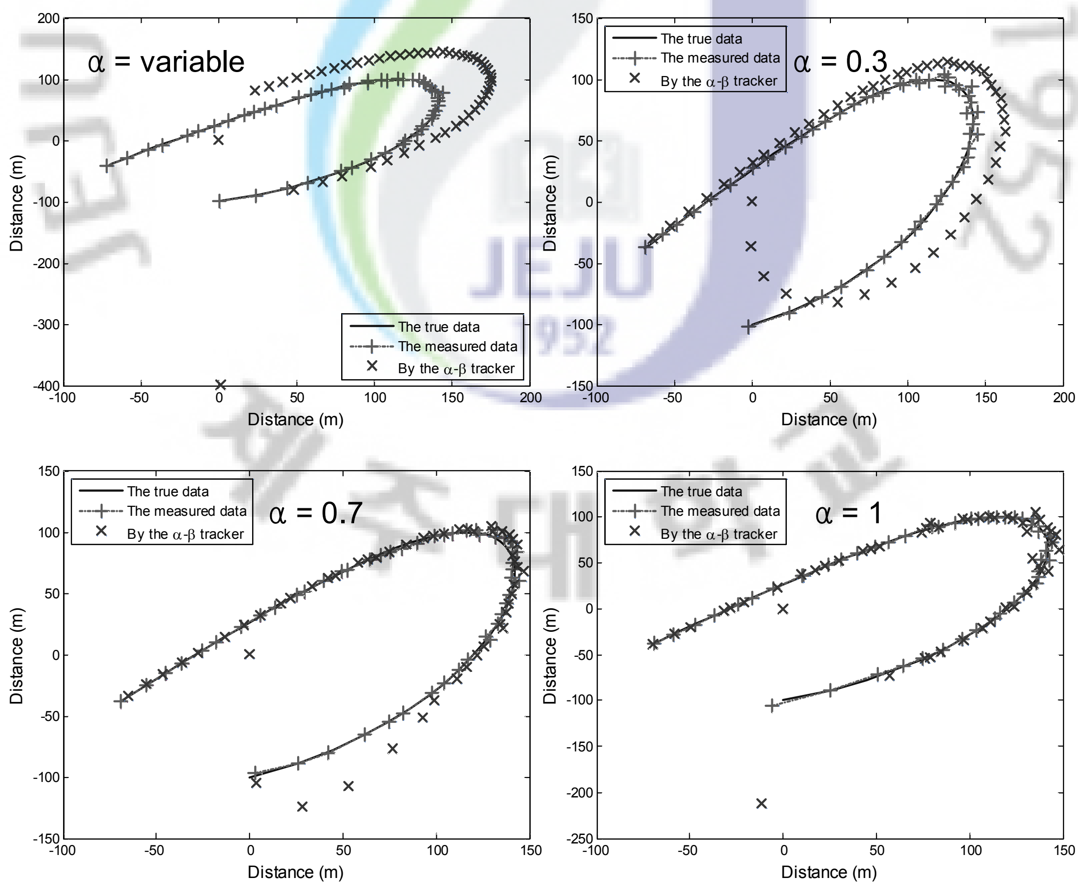

Figure 2-3. Attained simulation results of the α-β tracker.

Fig. 2-3 shows the effect of varying the coefficient α. From the Fig. 2-3, the α-β tracker shows the best tracking performance when the coefficient α is a variable in case of the non-linear moving target model (Model II). However, the α-β tracker lost a target when the coefficient α is a variable. Using (2-5), the errors are calculated for the four different values of the coefficient α, 0.3, 0.7, 1 and the variable from (2-3). The error curves by the coefficient α are as shown in Fig. 2-4.

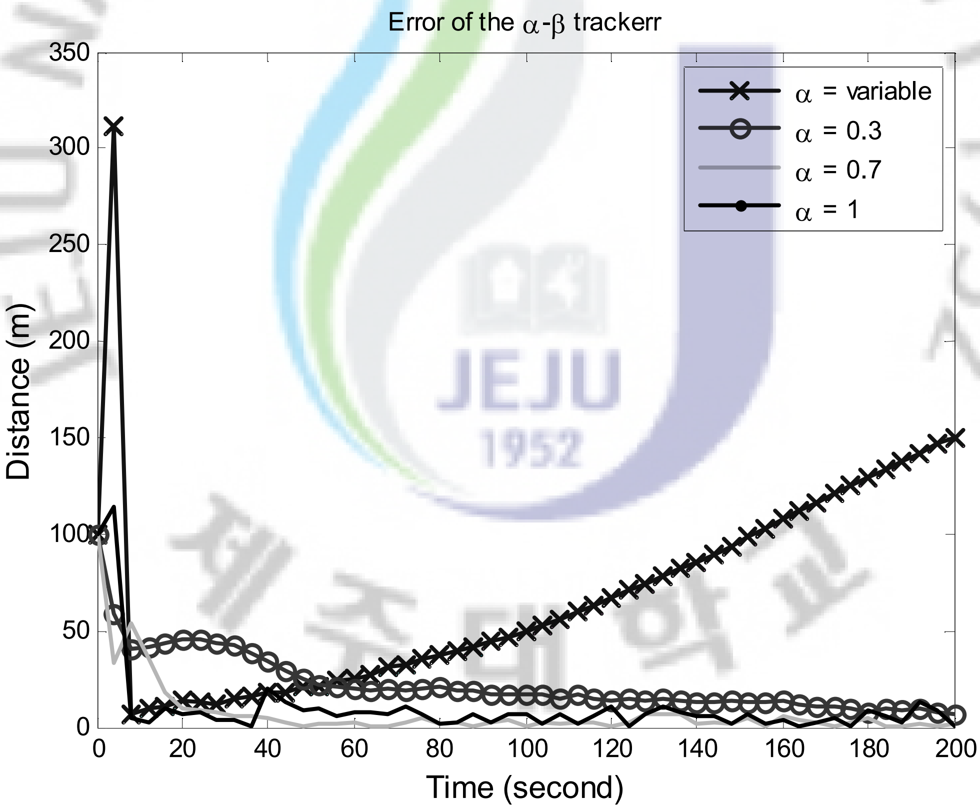

Figure 2-4. The error curves by the coefficient α

As shown in Fig. 2-4, the error of the α-β tracker is increased monotonically with time when the coefficient α is a variable. The errors are given in Table 2-3.

Table 2-3. Error of the α-β tracker

α	variable	0.3	0.7	1
Error	3560.9	1178.5	397.0	497.7

From the table 2-3, a variable coefficient is not suitable in case of the non-linear moving target model (Model II). And when coefficient α is 0.7, the α-β tracker gives the best tracking performance.

2.2.2 The Kalman Tracker

The state equation of a target is given by [16]

$$X_{k+1} = FX_k + W_k \tag{2-6}$$

where $X_k = \begin{bmatrix} x_k & y_k & \dot{x}_k & \dot{y}_k \end{bmatrix}$ is state vector at time k. x_k, y_k and $\dot{x}_k$, $\dot{y}_k$ represent the positions and speeds in x, y coordinates, respectively.

The transition matrix F is given by

$$F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-7}$$

where T is the sampling interval and W_k is the process noise vector with covariance matrix Q.

The measurement equation is

$$z_k(k) = HX_k + V_k \tag{2-8}$$

where V_k is the measurement noise vector with covariance matrix R which is assumed to be white with zero mean, and no correlation exists with W_k

The measurement matrix H is given by

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{2-9}$$

The predicted estimate time update equations are

$$\hat{\underline{x}}_{k-1} = F\hat{\underline{x}}_{k-1}$$
$$P_{k-1} = FP_{k-1}F^T + Q_{k-1} \tag{2-10}$$

where P_{k-1} is estimation error covariance matrix.

The filtered estimate measurement update equations are

$$\hat{\underline{x}}_k = \hat{\underline{x}}_{k-1} + K_k(z_k - H\hat{\underline{x}}_{k-1})$$
$$P_k = P_{k-1} - P_{k-1}H^T \mathrm{Re}_k^{-1} HP_{k-1} \tag{2-11}$$

where the Kalman gain matrix is defined as

$$\mathrm{Re}_k = HP_{k-1}H^T + R$$
$$K_k = P_{k-1}H^T (\mathrm{Re})^{-1} \tag{2-12}$$

and estimation error covariance is given by

$$P_k = (I - K_k H_k)P_{k-1} \tag{2-13}$$

The Kalman tracking algorithm can be denoted as follows:

Procedure {Design Algorithm of the Kalman tracker}

Generate the measured position $z(N)$

Set the number of iteration of the Kalman tracker ***N***;

Set the initial state vector $\hat{\underline{x}}_0$;

Set the measurement noise covariance ***R*** and the process noise covariance ***P***, ***Q***;

Set the transition matrix ***F*** and the measurement matrix ***H***;

For *k=1, 2, …, N*

Extrapolate the most recent state estimate to the present time;

Compute the Kalman gain;

Update the state estimate;

Compute the covariance of the estimation error

End

Example III: Tracking a linear moving target model (Model I) using the Kalman tracker

The Kalman tracker is operated for the four different values of the noise variance Q, 1, 0.1, 0.01 and 0.001. In the simulation, the Gaussian noise used is same as in ***Example I***. Fig. 2-5 illustrates the tracking when a target has a sharp turn trajectory with constant velocity.

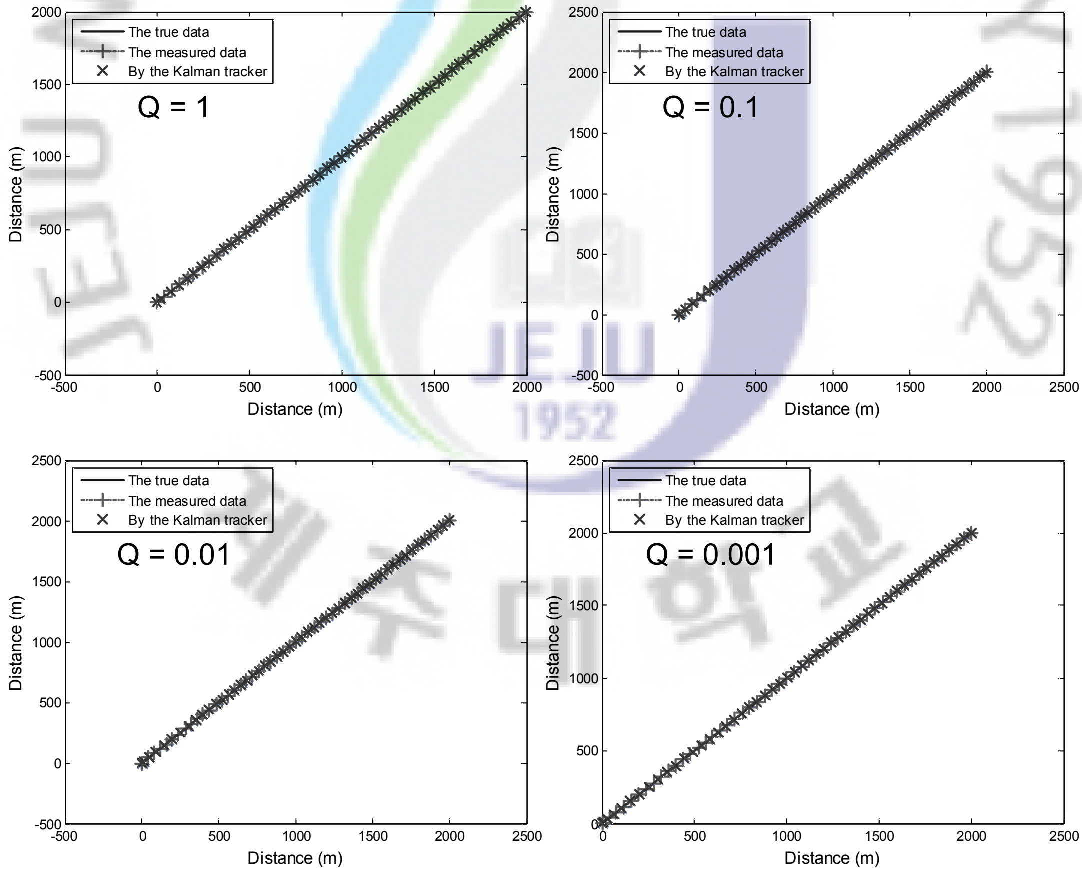

Figure 2-5. Attained simulation results of the Kalman tracker

From the results, the Kalman tracker shows good tracking performance for the linear moving target model (Model I). Using (2-5), the errors are calculated for the four different values of the noise covariance Q, 1, 0.1, 0.01 and 0.001. The error curves by the noise covariance Q are as shown in Fig. 2-6.

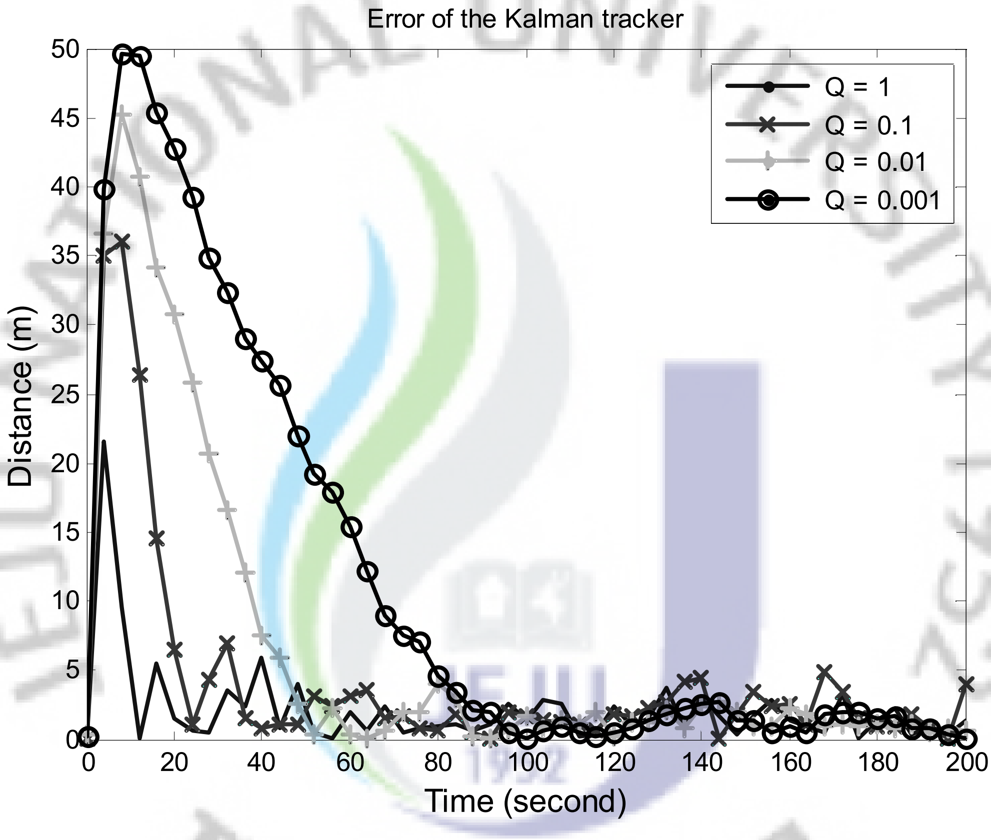

Figure 2-6. The error curves by the noise covariance

As shown in Fig. 2-6, the Kalman tracker shows the best tracking performance when the noise variance Q is 1, in case of the linear moving target model (Model I).

Table 2-4, Error of the Kalman tracker

Q	**1**	**0.1**	**0.01**	**0.001**
Error	144.8	241.1	648.4	1298.3

From the table 2-4, as the noise covariance Q decreases, the error of the Kalman tracker tends to increase.

Example IV: Tracking a non-linear moving target model (Model II) using the Kalman tracker

The Kalman tracker is operated for the four different values of the noise variance Q, 1, 0.1, 0.01 and 0.001. In the simulation, the Gaussian noise used is same as in ***Example I***. Fig. 2-7 illustrates the tracking when a target has a sharp turn trajectory with variable velocity.

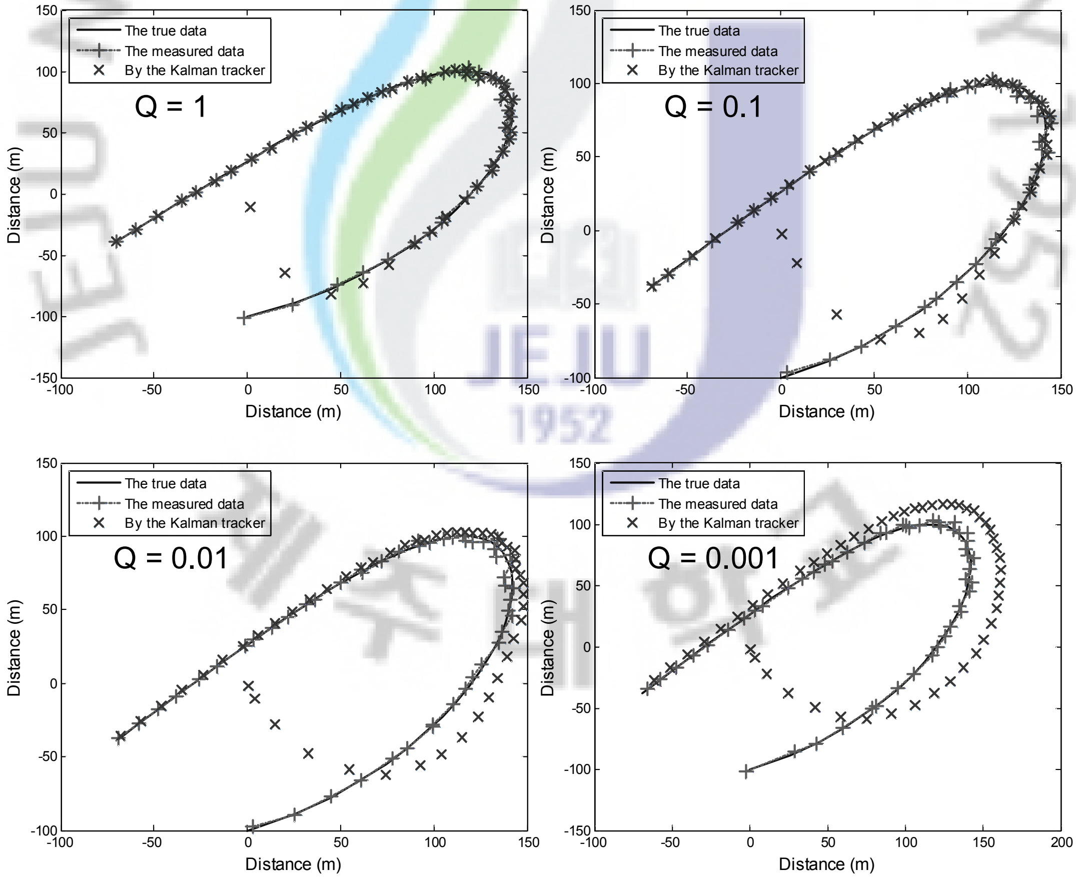

Figure 2-7. Attained simulation results of the Kalman tracker

From the results, the Kalman tracker shows the best tracking performance when the noise covariance Q is 1. However, the Kalman tracker lost a target when the noise covariances Q are 0.1, 0.01 and 0.001. Using (2-5), the errors are calculated for the four different values of the noise covariance Q, 1, 0.1, 0.01 and 0.001. The error curves by the noise covariance Q are as shown in Fig. 2-8.

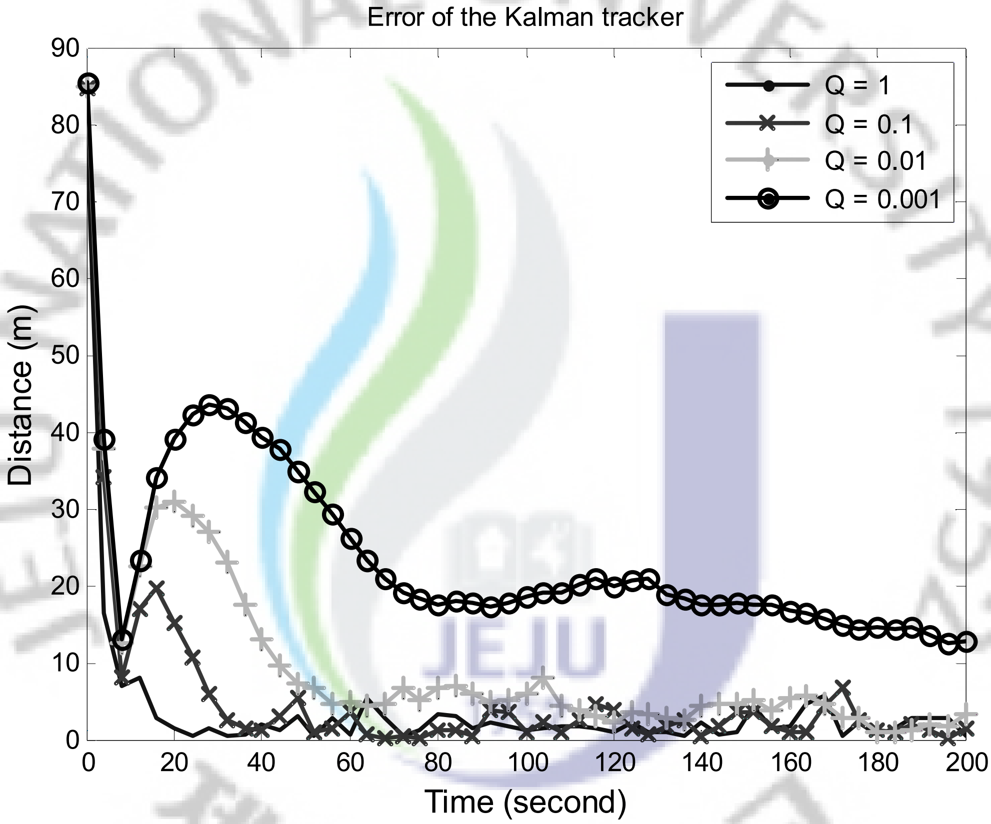

Figure 2-8. The error curves by the noise covariance

As shown in Fig. 2-8, the Kalman tracker shows the best tracking performance when the noise variance Q is 1 in case of the linear moving target model (Model I). The errors are given in Table 2-5.

Table 2-5. Error of the Kalman tracker

Q	1	0.1	0.01	0.001
Error	225.9	338.8	627.1	1338.3

From the table 2-5, the Kalman tracker shows the best tracking performance when the noise covariance Q is 1. However, the Kalman tracker lost a target in case of noise covariance Q is 0.001 for a non-linear moving target model (Model II).

2.3 Proposed Algorithm

2.3.1 The Switched Slide Window Tracker

The switched slide window tracker (SSWT) is composed of the α-β tracker to find the initial parameters and slide window tracker (SWT) to track the targets. Fig. 2-9 shows the flow chart of the proposed SSWT. First of all, the α-β tracker is running until the initial parameters for a particular window size are obtained. Then the slide window tracker predicts the next position using the weight value and the previously estimated position.

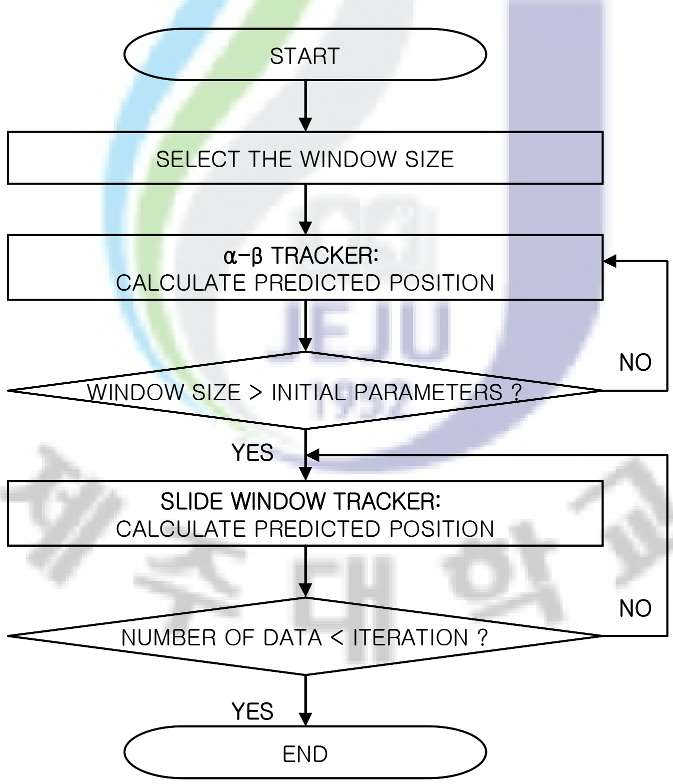

Figure 2-9. Flow chart for the SSWT

The initial values are estimated by using the α-β tracker defined in (2-1).

The SSWT is designed exploiting a piecewise linear model for a moving target. If a piecewise linear model is used during the short time of a trajectory, the non-linear model can be treated as a linear model as shown in Fig. 2-10.

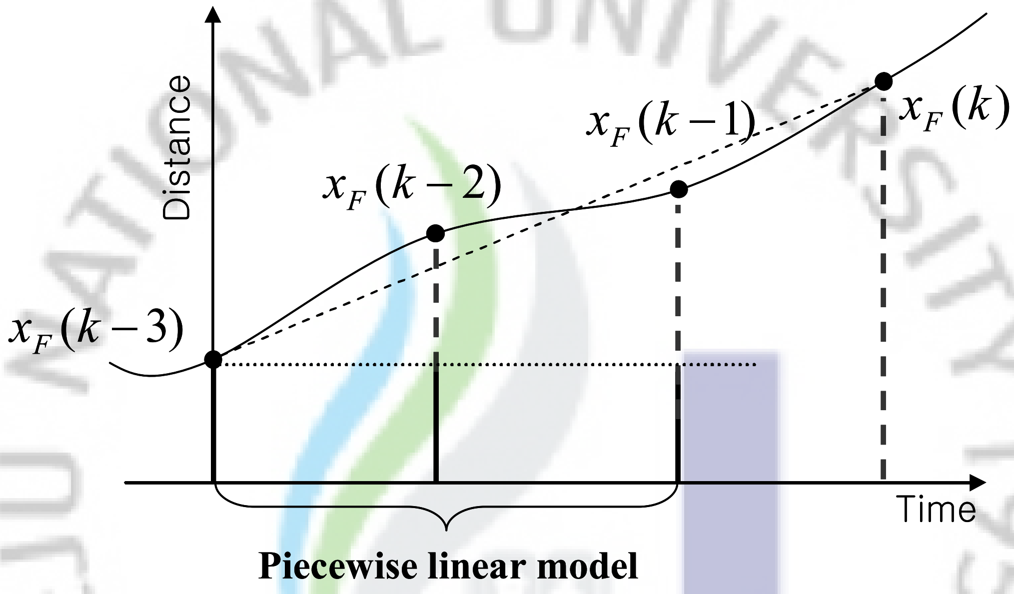

Figure 2-10. A piecewise linear model for non-linear moving target

Using the piecewise linear model, assume that our trajectory is satisfied as piecewise linear moving at the same interval. The target position could be predicted by the present estimated position. If the target position varies linearly, the predicted target position can be expressed by the linear combination of the previously estimated position [7].

When initial positions are obtained greater than the window size, the process is switched to SWT from the α-β tracker. The SWT can be defined by following equations:

$$X_F(k) = x_p(k) + \mu[x_m(k) - x_p(k)],$$
$$x_p(k+1) = x_F(k-M) + \sum_{m=1}^{M} \omega_m [x_F(k-m+1) - x_F(k-M)], \tag{2-14}$$

where $x_m(k)$ is the x coordinate of the target's measured position, $x_p(k+1)$ is the x coordinate of the target's predicted position, $x_F(k)$ is the x coordinate of the filtered target position, ω_m is the weight value [10], and μ is the coefficient for the measurement update of the slide window tracker (In the thesis, $\mu = \alpha$.). From (2-14), we can easily extend the equation for a 2-D problem.

In the thesis, weight values ω_m are obtained for window size M=2, 3, 4 and 5 and the results are shown in Table 2-6.

Table 2-6. The weight values

Weight value	**Window size**				
	ω_1	ω_2	ω_3	ω_4	ω_5
2	-1	2			
3	-2/3	1/3	4/3		
4	-0.5	0	0.5	1	
5	-0.35	-0.2	0.25	0.5	0.8

Computer simulation was done to prove the performance of the proposed algorithm. The proposed algorithm as described in Fig. 2-9 can be denoted as follows:

Procedure {Design Algorithm of the SSWT}

Generate the measured position $x_m(N)$;

Choose a window size M ($M = 2, 3, 4, 5$);

Set the number of iteration of the α-β tracker MM ($MM = M + 1$;

Set the initial position and velocity for α-β tracker;

Select the α-β coefficients;

For k=1, 2, …, MM

Compute initial positions using the α-β tracker in (2-1);

End

For k=MM+1, MM+2, …, N

Switch to SWT;

Compute the predicted positions using (2-14);

End

For an α-β tracker, the criterion for selecting the α-β coefficients is based on the best linear track fitted to radar data in a least squares sense. The α-β coefficients is given by [4]

$$\alpha = (2(2k-1))/(k(k+1)). \tag{2-15}$$

$$\beta = 6/(k(k+1)). \tag{2-16}$$

where k is the number of the scan or target observation (k>2).

In the simulation, the radar measures the positions of the moving target once per second, and 200 iterations was performed. The window size for the SWT is M=2, 3, 4, 5. Two target models, a linear moving target model and a non-linear moving target models are used to verify the proposed algorithm.

Example V: Tracking a non-linear moving target model (Model I) using the SSWT

The SSWT is operated for the four different values of the window size *M*, 2, 3, 4 and 5. In the simulation, the Gaussian noise used is same as in ***Example I***. Fig. 2-11 illustrates the tracking when a target has a straight trajectory with constant velocity.

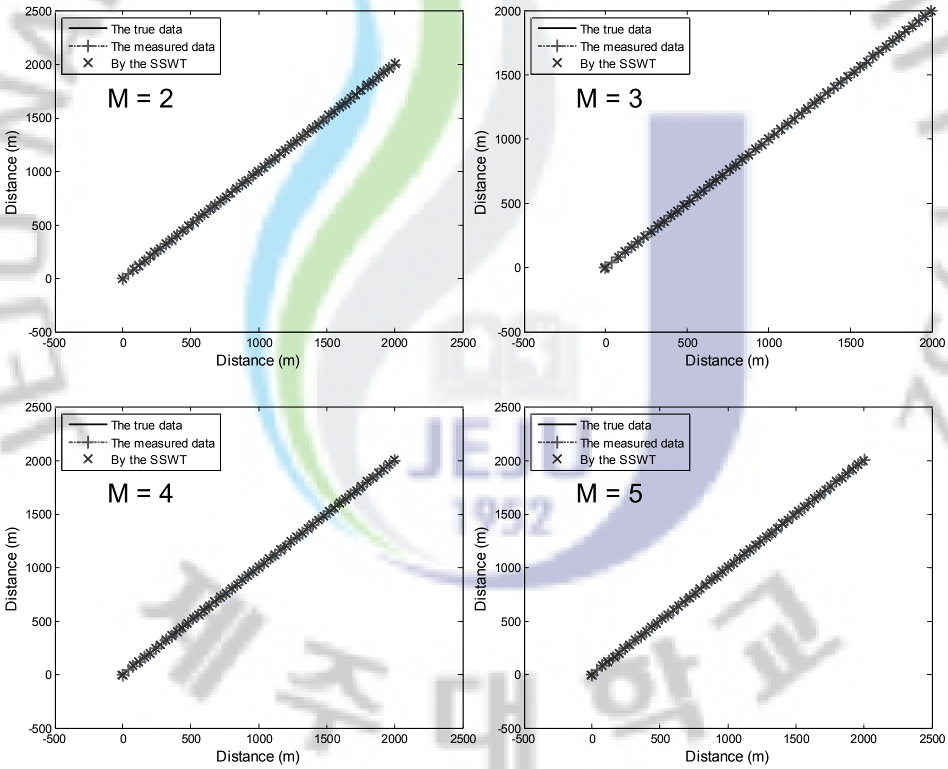

Figure 2-11. Attained simulation results of the SSWT

As shown in Fig. 2-11, the SSWT shows good tracking performance for a linear moving target model (Model I). Using (2-5), the errors are calculated for the four different values of the window size *M*, 2, 3, 4 and 5. The error curves by the window size *M* are as shown in Fig. 2-12.

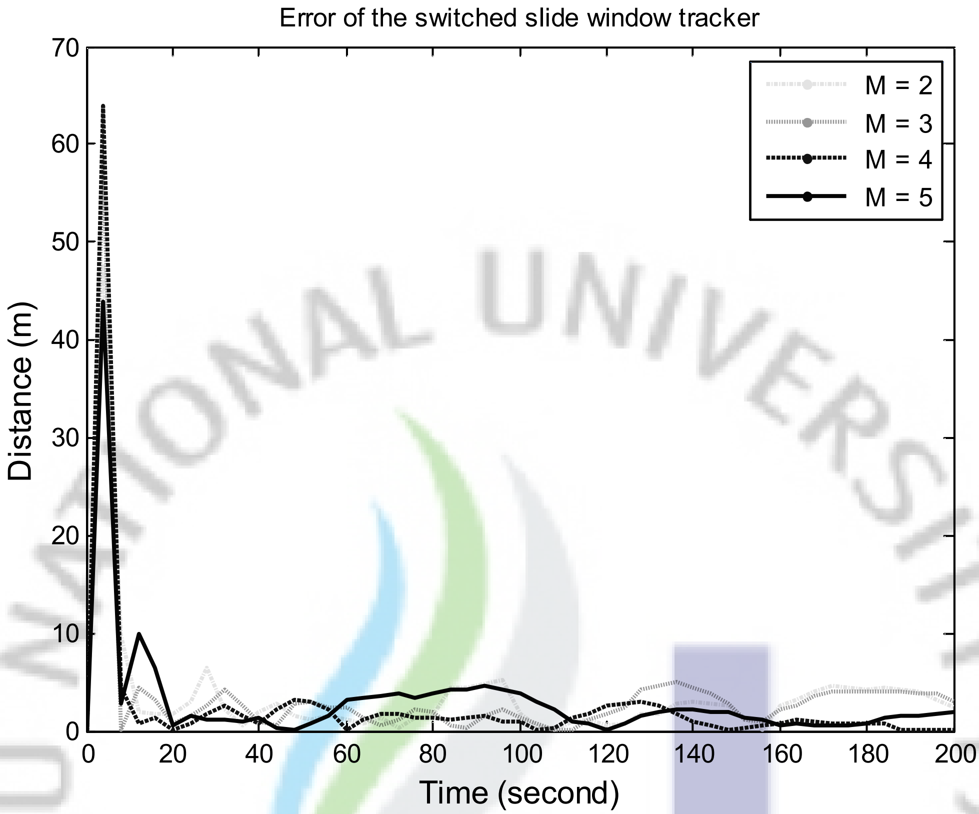

Figure 2-12. The error curves by the window size.

As shown in Fig. 2-12, the SSWT shows good tracking performance for a linear moving target model (Model I). The errors are given in Table 2-7.

Table 2-7. Error of the switched slide window tracker

M	2	3	4	5
Error	187.5	138.7	154.1	129.7

From the table 2-7, a small window size gives a better tracking performance for a linear moving target model (Model I).

Example VI: Tracking a non-linear moving target model (Model II) using the SSWT

The SSWT is operated for the four different values of the window size *M*, 2, 3, 4 and 5. In the simulation, the Gaussian noise used is same as in ***Example I***. Fig. 2-13 illustrates the tracking when a target has a sharp turn trajectory.

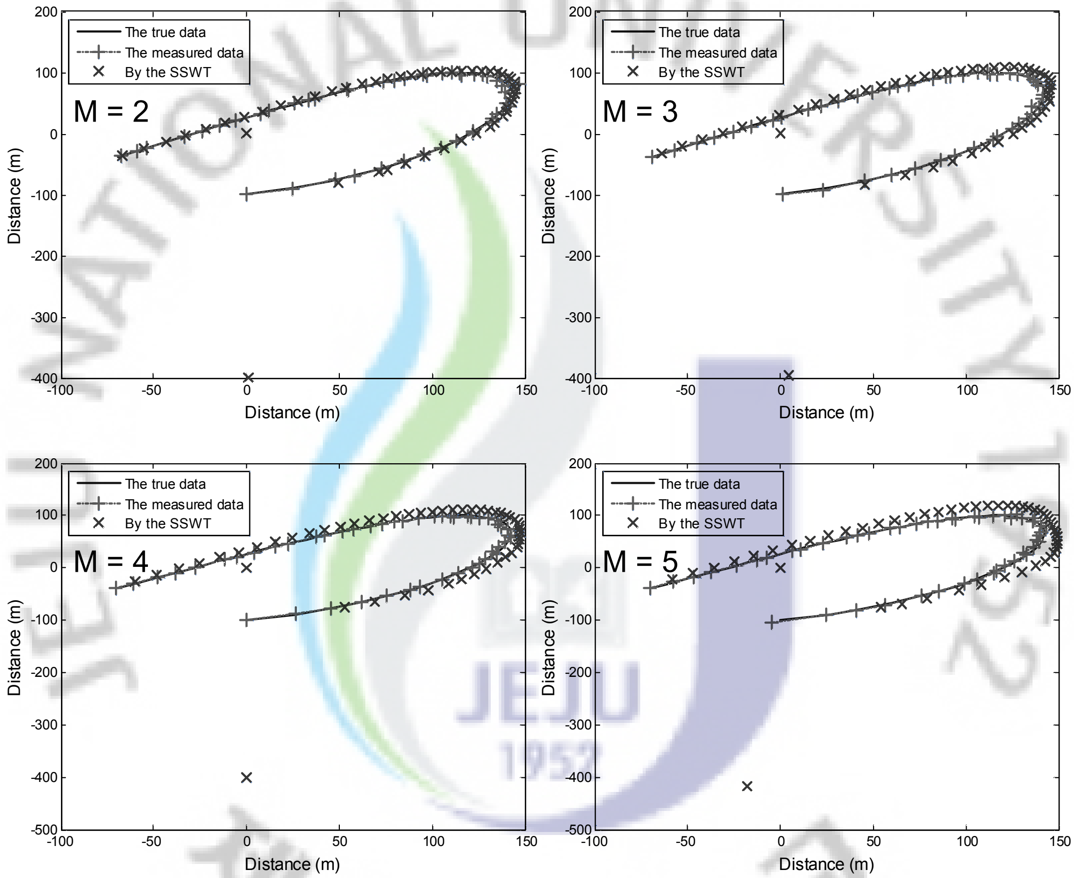

Figure 2-13. Attained simulation results of the SSWT

As shown in Fig.2-13, the SSWT shows the best tracking performance when the window size *M* is 2. Using (2-5), the errors are calculated for the four different values of the window size *M*, 2, 3, 4 and 5. The error curves by the window size *M* are as shown in Fig. 2-14.

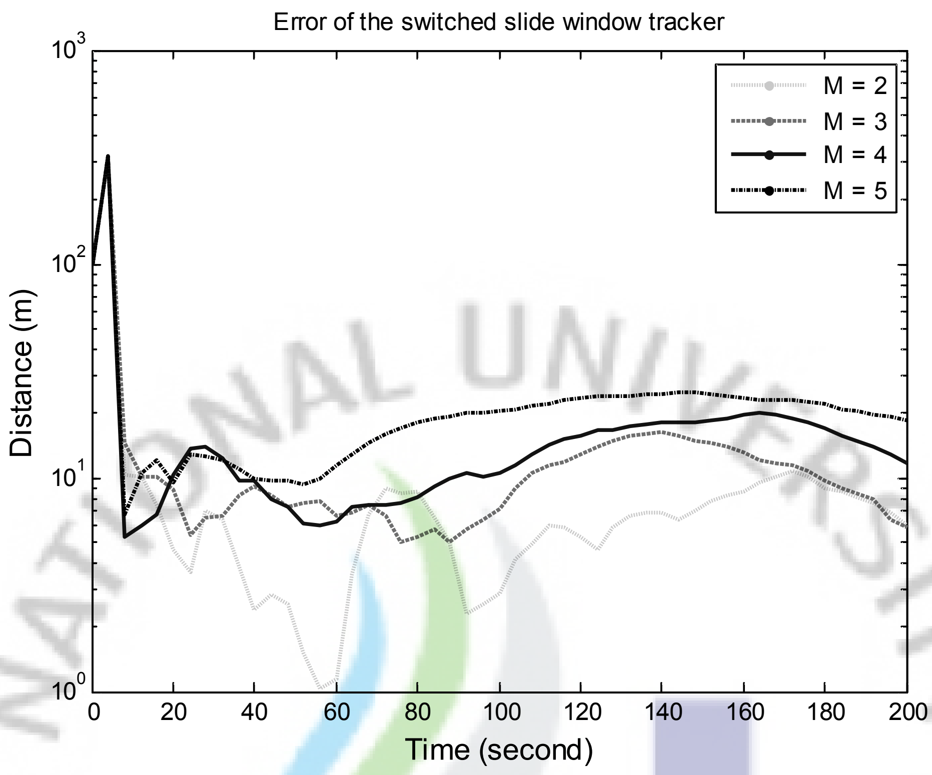

Figure 2-14. The error curves by the window size.

From the table 2-8, the SSWT shows the best tracking performance when the window size *M* is 2, in case of a non-linear moving target model (Model II).

Table 2-8. Error of each tracking algorithm

M	2	3	4	5
Error	677.5	816.9	1072.3	1306.7

From the results, the SSWT shows better tracking performance when the window size *M* is small in case of a non-linear moving target. The errors are given in Table 2-8.

2.3.2 Comparison of Each Algorithm

In this simulation, the target model II and III are used for comparison. In the simulation, the Gaussian noise used is same as in ***Example I***.

Fig. 2-15 illustrates the tracking results by changing the coefficient α of the α-β tracker for a non-linear moving target model (Model II). The coefficient β is obtained from (2-4). The noise covariance Q of the Kalman tracker and window size M of the SSWT are set as 1 and 2, respectively.

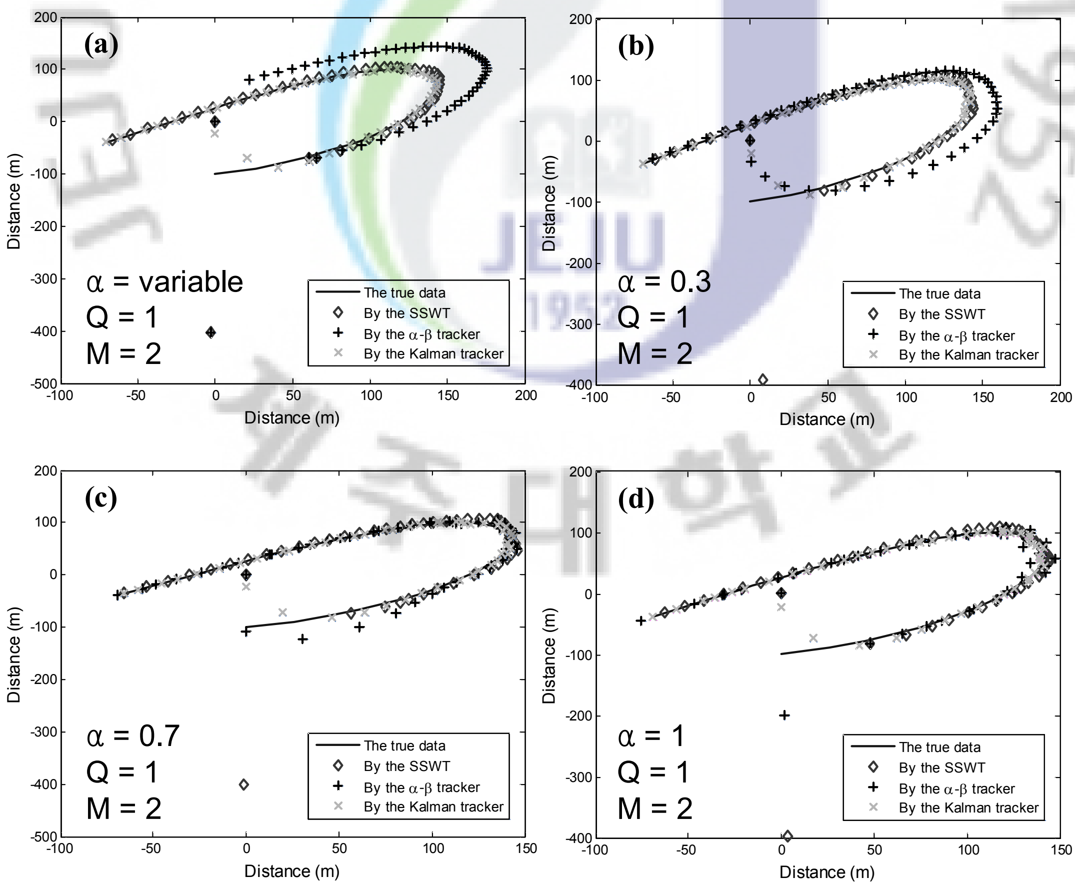

Figure 2-15. The trajectory of each algorithm

As shown in Fig. 2-15, the Kalman tracker and the SSWT give good tracking performance for a non-linear moving target model (Model II). To compare the tracking performance of each algorithm, the errors are calculated using (2-5). The error curves of each tracking algorithm are as shown in Fig. 2-16.

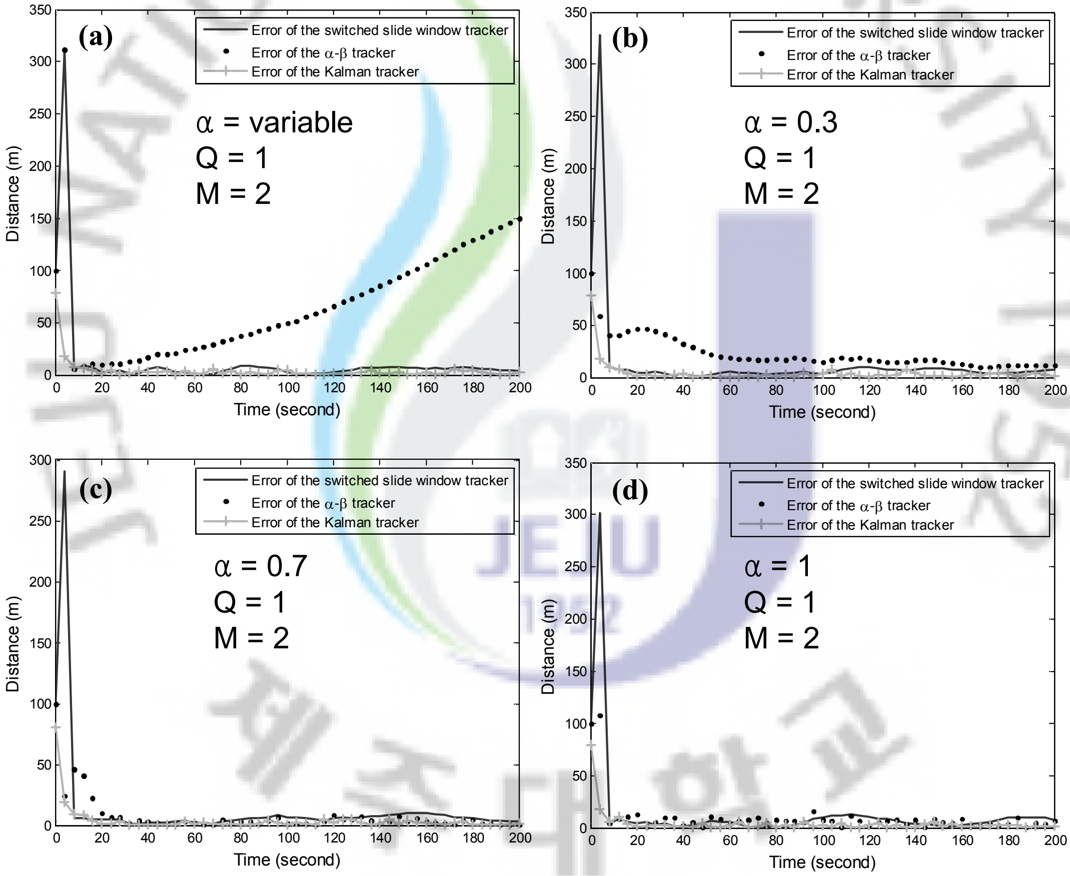

Figure 2-16. The error curves of each algorithm

As shown in Fig. 2-16, the α-β tracker gives the worst tracking result when the coefficient α is a variable. The errors of each algorithm are given in Table 2-9.

Table 2-9. Error of each tracking algorithm

Type of algorithm	Error			
	(a)	(b)	(c)	(d)
The SSWT	629.2	653.1	728.2	723.3
The α-β tracker	3486.4	1152.8	426.7	525.4
The Kalman tracker	196.7	204.1	224.8	221.2

From the table 2-9, the Kalman tracker gives the best tracking performance in case of a non-linear moving target model (Model II).

Fig. 2-17 illustrates the tracking results by changing the noise covariance Q of the Kalman tracker for a non-linear moving target model (Model II). The coefficient β is obtained from (2-4). The coefficient α of the α-β tracker and window size M of the SSWT are set as the variable obtained from (2-3) and 2, respectively.

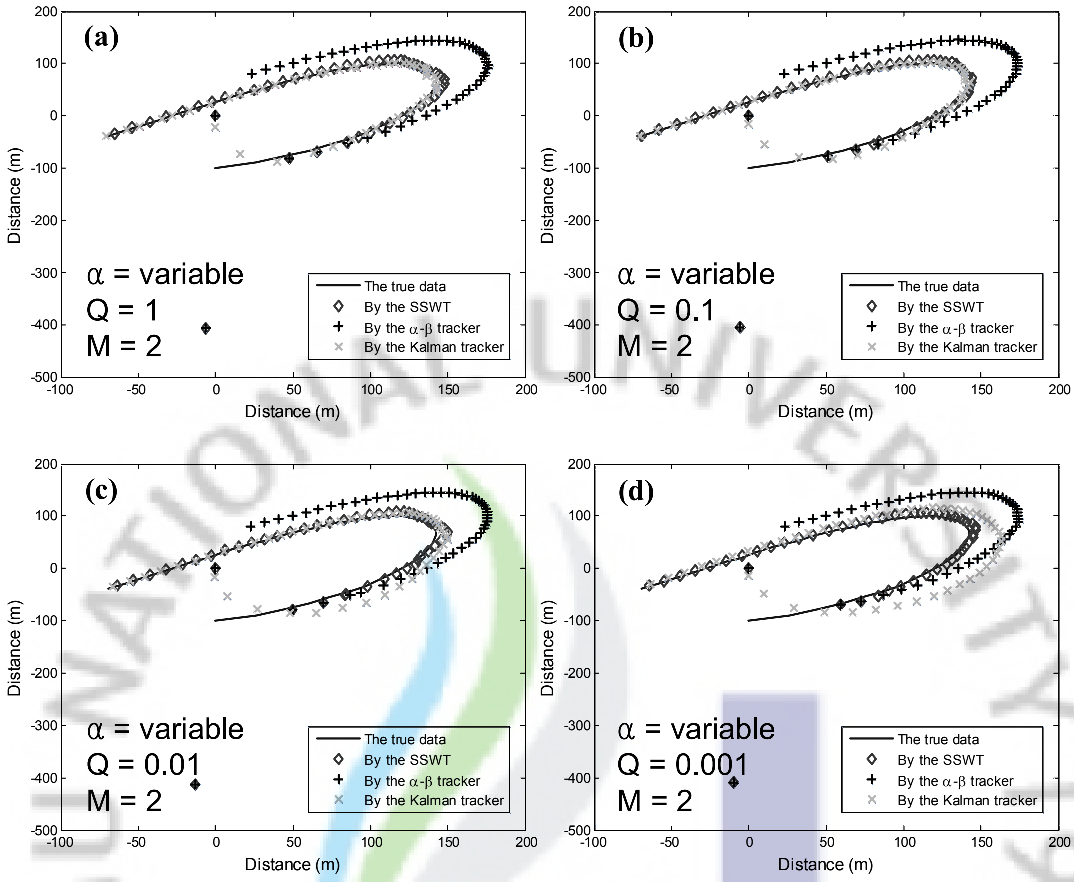

Figure 2-17. The trajectory of each algorithm

As shown in Fig. 2-17, the SSWT gives good tracking performance for a non-linear moving target model (Model II). To compare the tracking performance of each algorithm, the errors are calculated using (2-5). The error curves of each tracking algorithm are as shown in Fig. 2-18.

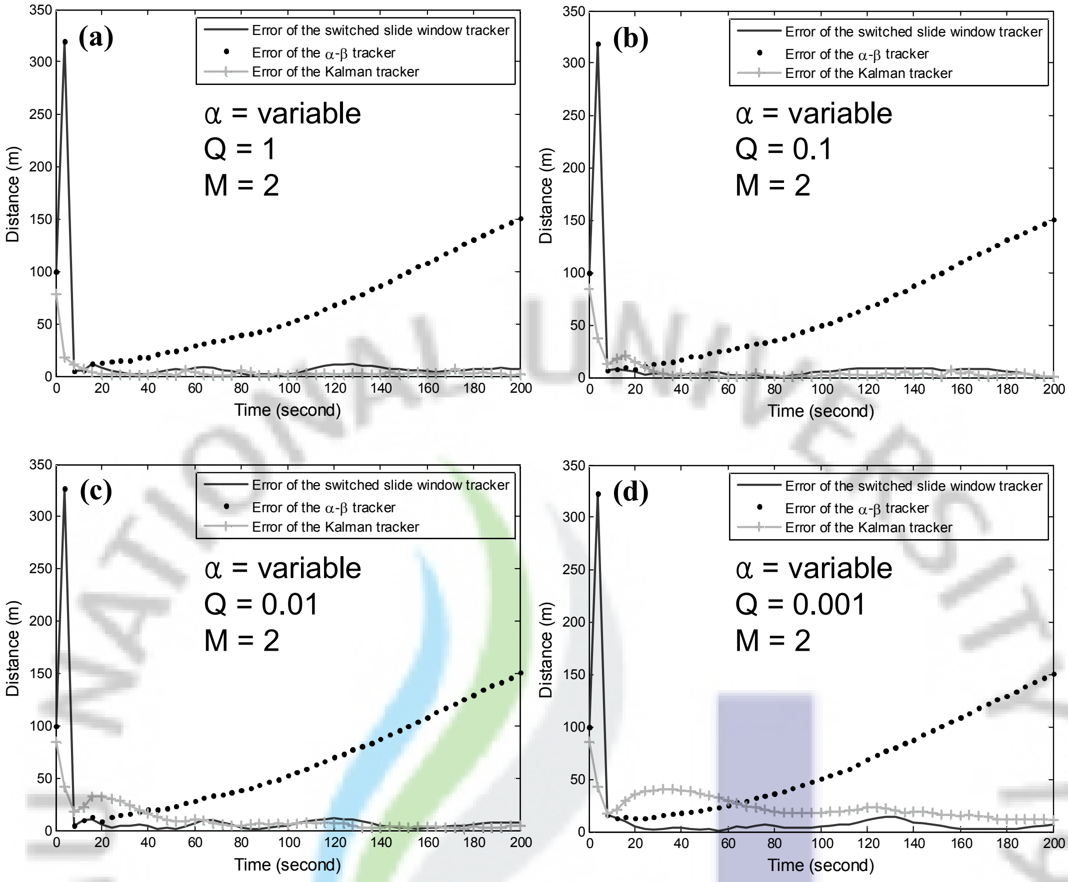

Figure 2-18. The error curves of each algorithm

As shown in Fig. 2-18, the α-β tracker gives the worst tracking result. The errors of each algorithm are given in Table 2-10.

Table 2-10. Error of each tracking algorithm

Type of algorithm	Error			
	(a)	(b)	(c)	(d)
The SSWT	691.6	674.7	699.4	668.9
The α-β tracker	3558.9	3537.1	3547.8	3561.1
The Kalman tracker	203.3	291.4	558.6	1194.1

From the table 2-10, the Kalman tracker and the SSWT give the good tracking performance in case of a non-linear moving target model (Model II).

Fig. 2-19 illustrates the tracking results by changing the window size *M* of the SSWT for a non-linear moving target model (Model II). The noise covariance *Q* of the Kalman tracker and the coefficient α of the α-β tracker are set as 1 and the variable obtained from (2-3), respectively. The coefficient β is obtained from (2-4).

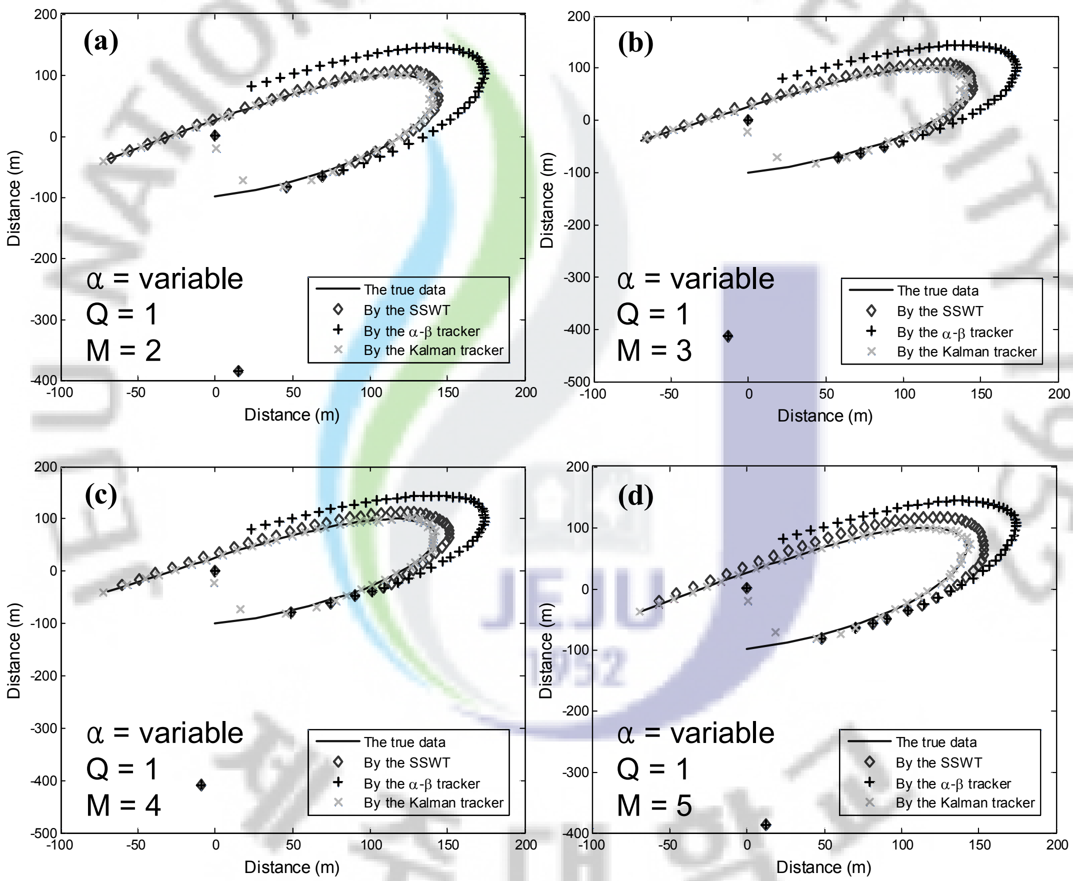

Figure 2-19. The trajectory of each algorithm

As shown in Fig. 2-19, the Kalman tracker and the SSWT give good tracking performance for a non-linear moving target model (Model II). To compare the tracking performance of each algorithm, the errors are calculated using (2-5). The error curves of each tracking algorithm are as shown in Fig. 2-20.

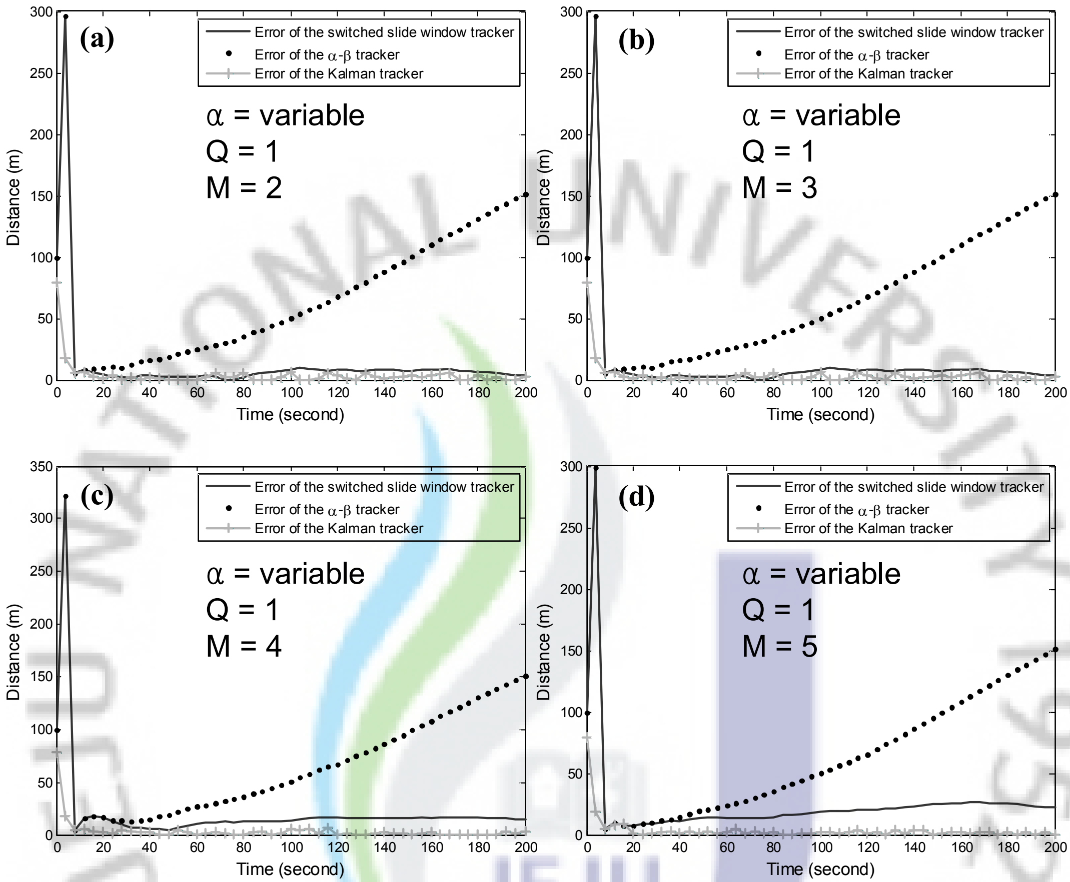

Figure 2-20. The error curves of each algorithm

As shown in Fig. 2-20, the α-β tracker gives the worst tracking result when the coefficient α is a variable. The errors of each algorithm are given in Table 2-11.

Table 2-11. Error of each tracking algorithm

Type of algorithm	Error			
	(a)	(b)	(c)	(d)
The SSWT	679.0	878.5	1076.0	1345.5
The α-β tracker	3558.9	3570.0	3582.8	3558.3
The Kalman tracker	226.8	209.0	215.4	210.2

From the table 2-11, the Kalman tracker and the SSWT give good tracking performance in case of a non-linear moving target model (Model II).

Fig. 2-21 illustrates the tracking results by changing the coefficient α of the α-β tracker for a non-linear moving target model (Model III). The coefficient β is obtained from (2-4). The noise covariance Q of the Kalman tracker and window size M of the SSWT are set as 1 and 2, respectively.

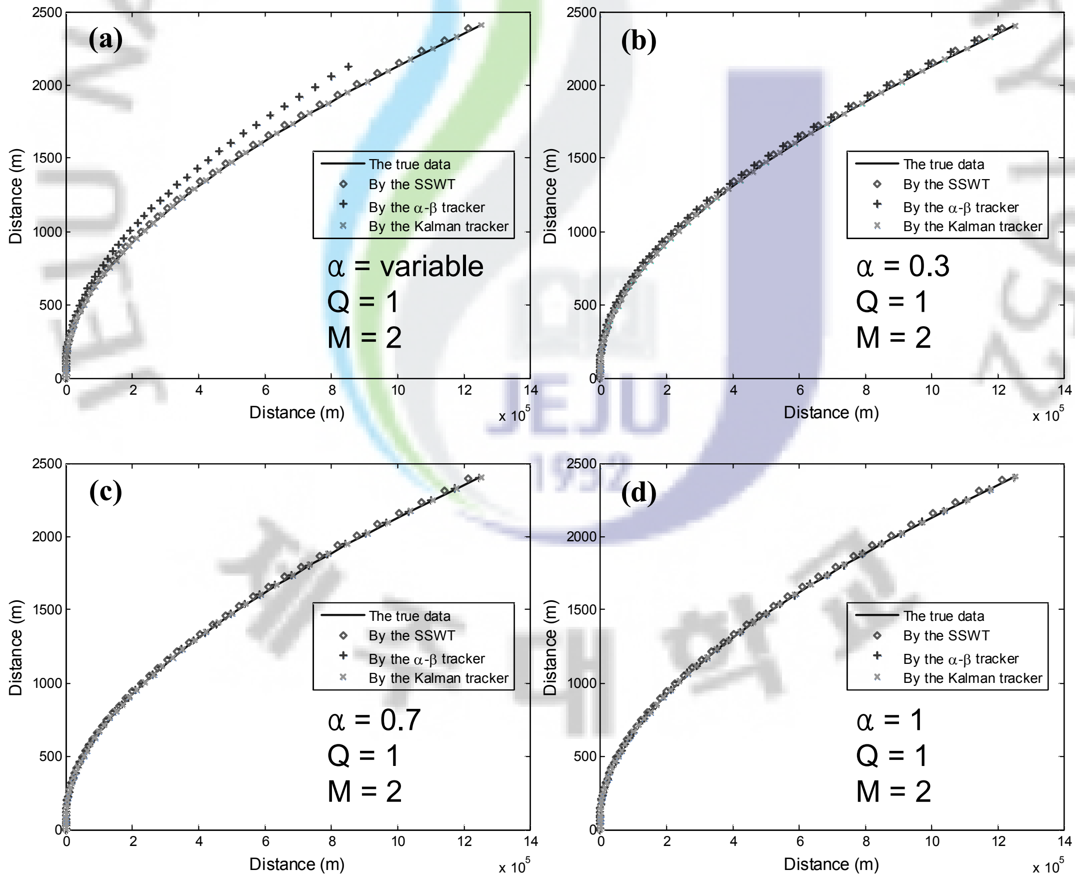

Figure 2-21. The trajectory of each algorithm

As shown in Fig. 2-21, the Kalman tracker and the SSWT give good tracking performance for a non-linear moving target model (Model III). To compare the tracking performance of each algorithm, the errors are calculated using (2-5). The error curves of each tracking algorithm are as shown in Fig. 2-22.

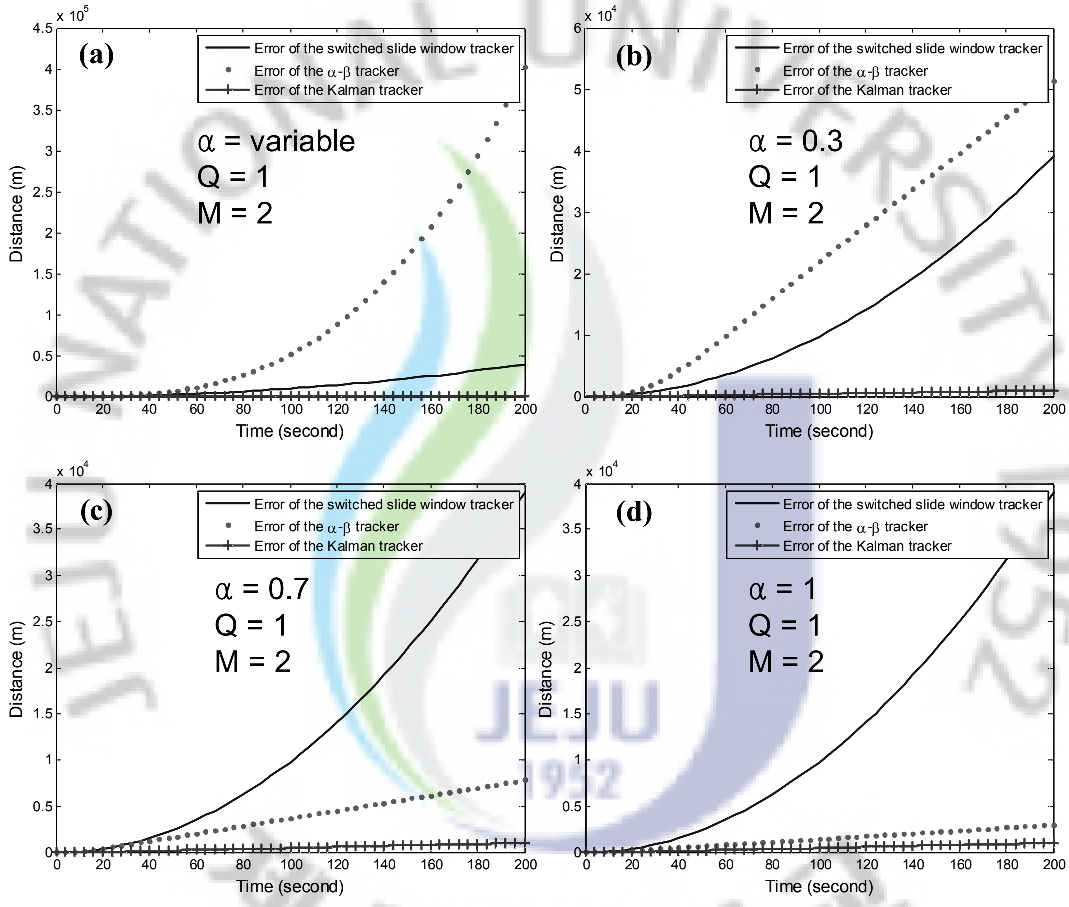

Figure 2-22. The error curves of each algorithm

As shown in Fig. 2-22, the Kalman tracker gives the best tracking result. The errors of each algorithm are given in Table 2-12.

Table 2-12. Error of each tracking algorithm

Type of algorithm	**Error**			
	(a)	**(b)**	**(c)**	**(d)**
The SSWT	671710	671720	671730	671730
The α-β tracker	5275300	1151000	190640	74448
The Kalman tracker	24833	24837	24840	24837

From the table 2-12, the Kalman tracker gives the best tracking performance in case of a non-linear moving target model (Model III).

Fig. 2-23 illustrates the tracking results by changing the noise covariance Q of the Kalman tracker for a non-linear moving target model (Model III). The coefficient α of the α-β tracker and window size M of the SSWT are set as the variable obtained from (2-3) and 2, respectively. The coefficient β is obtained from (2-4).

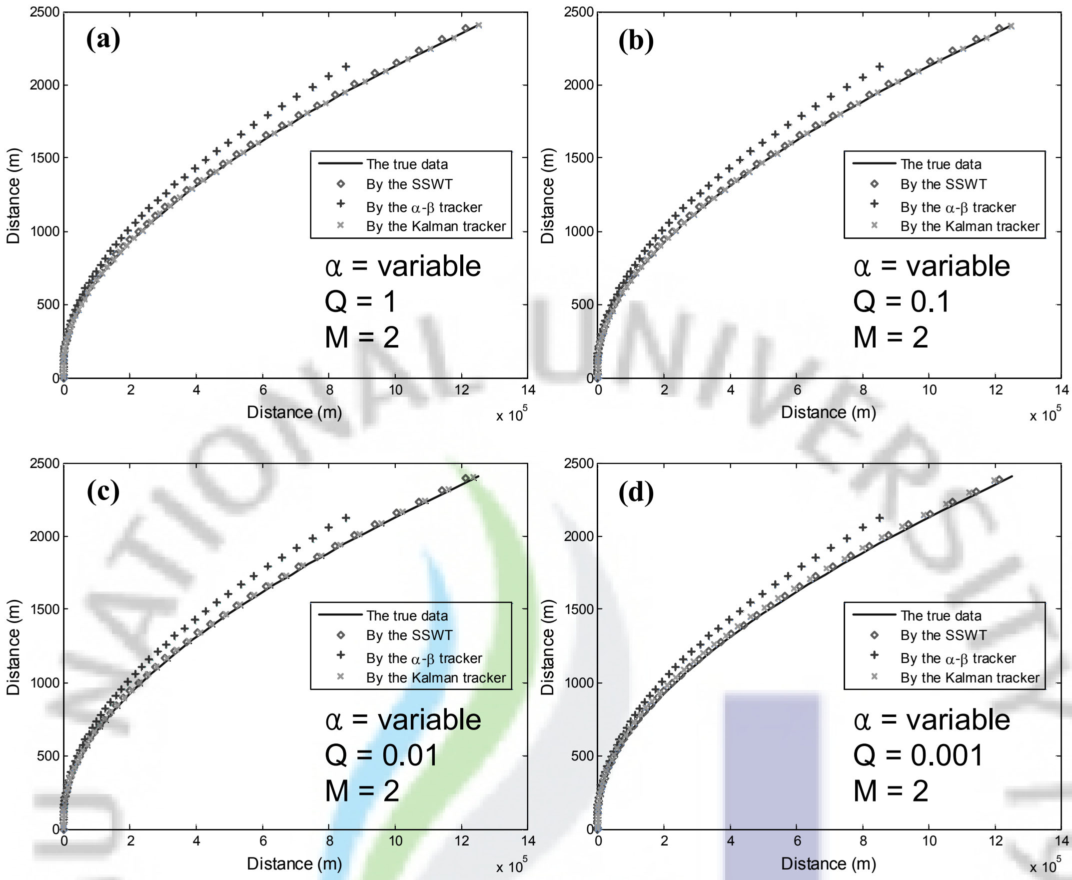

Figure 2-23. The trajectory of each algorithm

As shown in Fig. 2-23, the Kalman tracker and the SSWT give good tracking performance for a non-linear moving target model (Model III). To compare the tracking performance of each algorithm, the errors are calculated using (2-5). The error curves of each tracking algorithm are as shown in Fig. 2-24.

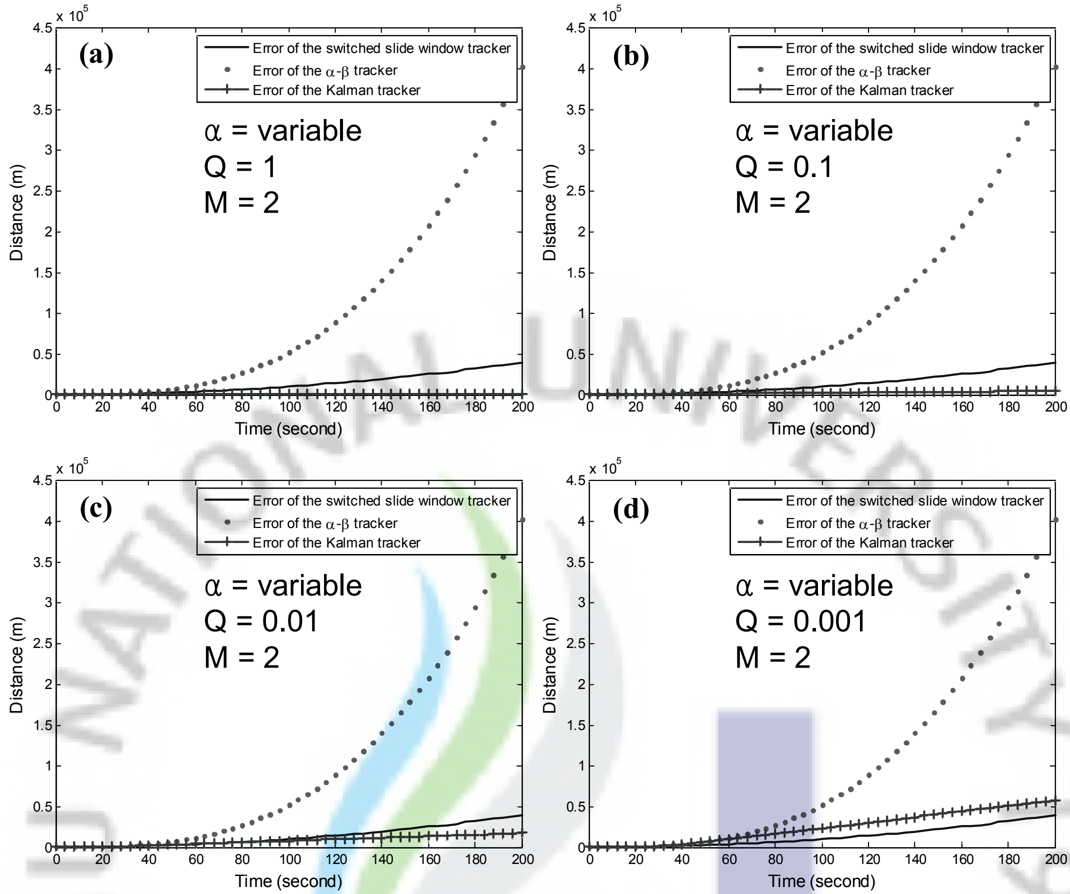

Figure 2-24. The error curves of each algorithm

As shown in Fig. 2-24, the α-β tracker gives the worst tracking result when the coefficient α is a variable. The errors of each algorithm are given in Table 2-13.

Table 2-13. Error of each tracking algorithm

Type of algorithm	Error			
	(a)	(b)	(c)	(d)
The SSWT	671710	671710	671730	671710
The α-β tracker	5275200	5275200	5275200	5275200
The Kalman tracker	24825	111390	401790	1235900

From the table 2-13, the Kalman tracker gives the best tracking performance in case of a non-linear moving target model (Model III).

Fig. 2-25 illustrates the tracking results by changing the window size *M* of the SSWT for a non-linear moving target model (Model III). The noise covariance *Q* of the Kalman tracker and the coefficient α of the α-β tracker are set as 1 and the variable obtained from (2-3), respectively. The coefficient β is obtained from (2-4).

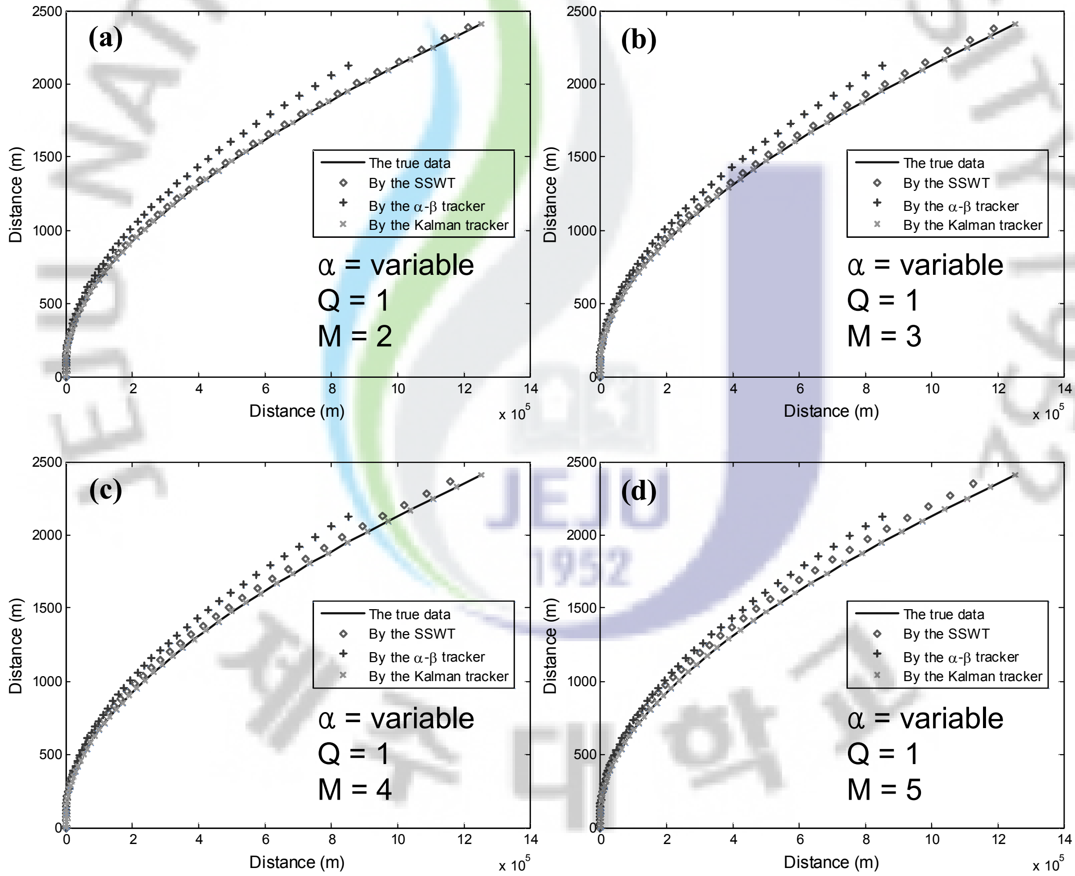

Figure 2-25. The trajectory of each algorithm

As shown in Fig. 2-25, the Kalman tracker and the SSWT give good tracking performance for a non-linear moving target model (Model III). To compare the tracking performance of each algorithm, the errors are calculated using (2-5). The error curves of each tracking algorithm are as shown in Fig. 2-26.

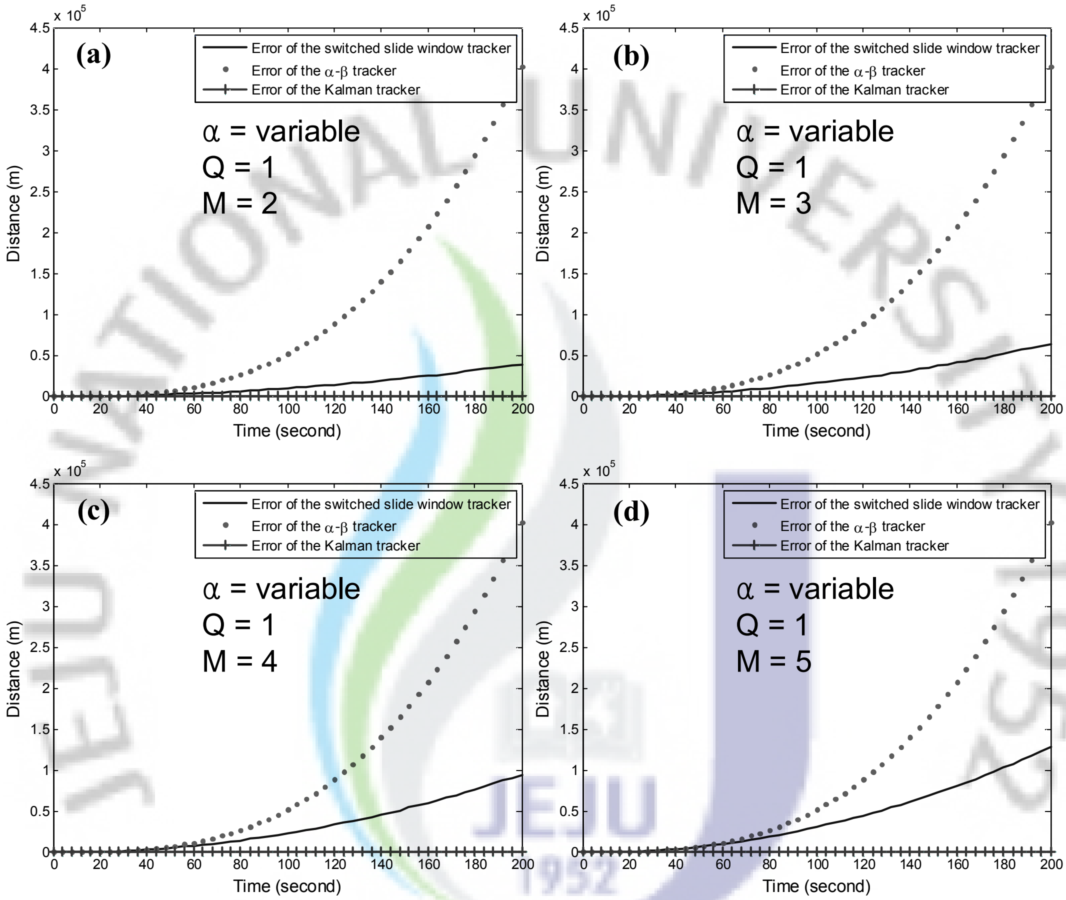

Figure 2-26. The error curves of each algorithm

As shown in Fig. 2-26, the α-β tracker gives the worst tracking result when the coefficient α is a variable. The errors of each algorithm are given in Table 2-14.

Table 2-14. Error of the each tracking algorithm

Type of algorithm	Error			
	(a)	(b)	(c)	(d)
The SSWT	671700	1093200	1595800	2139400
The α-β tracker	5275200	5275300	5275200	5275200

The Kalman tracker	24814	24819	24829	24814

From the table 2-14, the Kalman tracker gives the best tracking performance in case of a non-linear moving target model (Model III).

From all the results, on an average, the SSWT shows a good performance for not only a linear moving target model but also a non-linear moving target model. As shown in the all figures, the proposed method has better performance than the α-β tracker.

2.4 Implemented Simulator

The maritime radar simulator is made up of a DSP and a host PC. Fig. 2-27 illustrates the functional block diagram of the maritime radar simulator system.

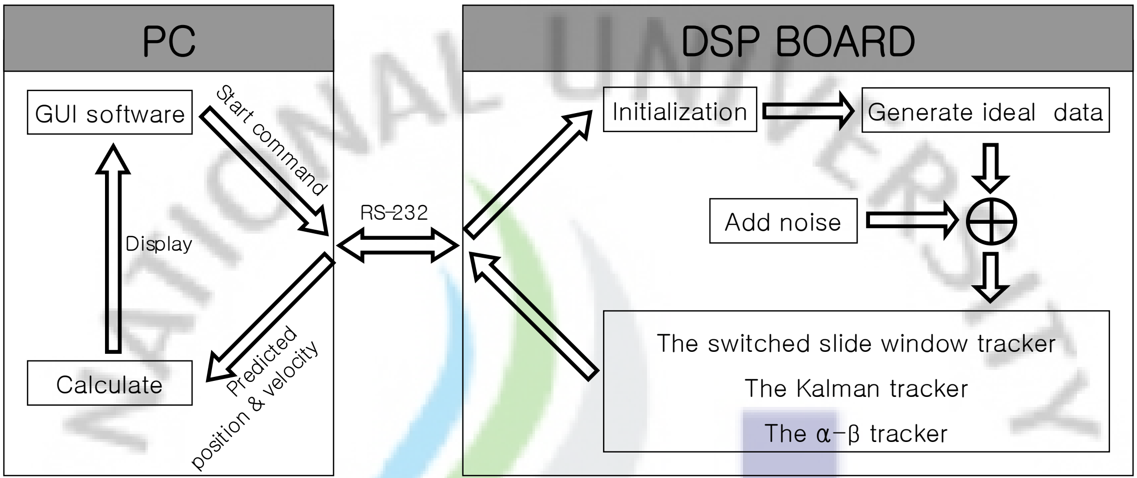

Figure 2-27. Block diagram of simulator

A TMS320C6711 DSP board was used to implement the maritime radar simulator for proposed tracking algorithm. The photograph of the DSP is shown in Fig. 2-28.

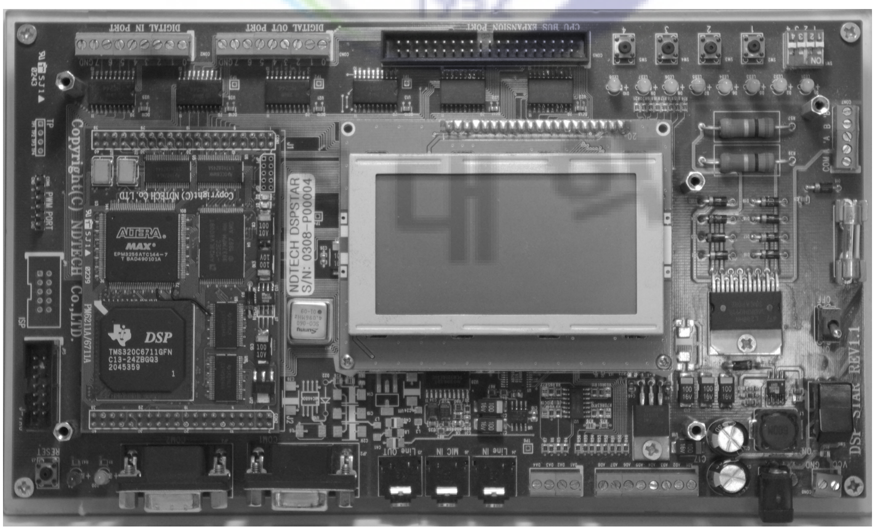

Figure 2-28. The DSP board.

A brief overview of the DSP board is shown in table 2-15.

Table 2-15. Specifications of the DSP board

DSP chip	TI TMS320C6711
Type	Floating Point DSP
Clock	200 MHz
ROM	1M Byte Flash Memory
Memory (SDRAM)	32M Byte
Internal Memory	64K Byte On-chip SRAM
EMIF	16-bit External Memory Interface
Serial Port	2 McBSP, User RS232, JTAG Port
Boot Mode	ROM Boot
Power	5V
Power Consumption	3.5 Watt

The DSP board has an SRAM that can be used to store programs and data. The instruction rate of the chip is 235 MIPS [17]. The DSP board performs the operations such as generation of actual data and tracking of maneuvering target. The DSP board is programmed so as to allow the user to select a tracking algorithm from the α-β tracker, the Kalman tracker and the SSWT. The DSP board tracks the predicted position and velocity using the selected tracking algorithm and data association. The data association is to get the firm track. If the host PC sends the predicted target of a track to the DSP board, the DSP chip sets a rough validation gate around the targets. If there are detects in the rough validation gate, the validated detects are sent back to the host PC. Then, PC sets a more refined validation gate on them, and chooses the best detect which will be used for the measurement update. The GUI software as shown in Fig. 2-29 is written by using LabVIEW 8.5.

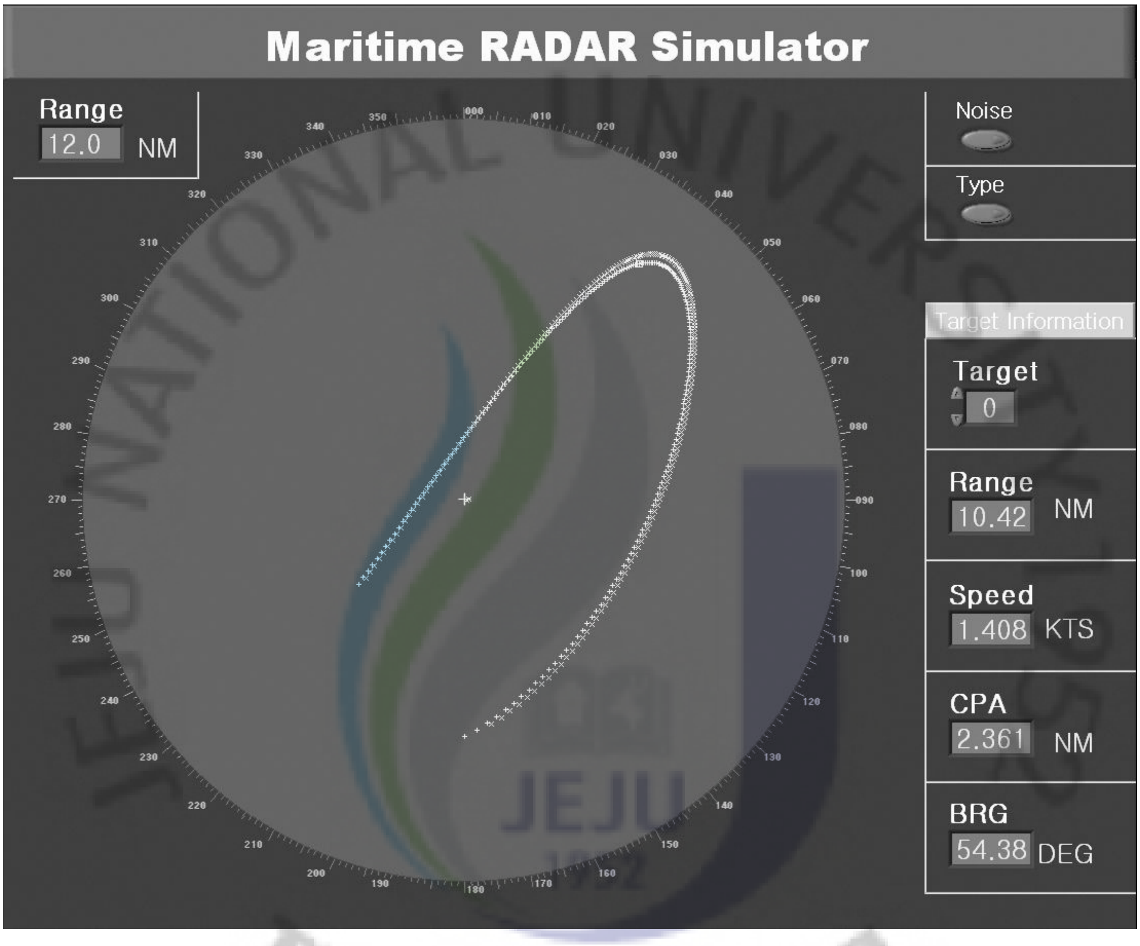

Figure 2-29. The maritime radar simulator

Using the obtained position and velocity from the DSP, the GUI in a host PC displays the information of the moving targets as follows [18]:

(1) Filtered range and bearing to the target,

(2) Predicted target range to the closest,

(3) True course and speed of the target.

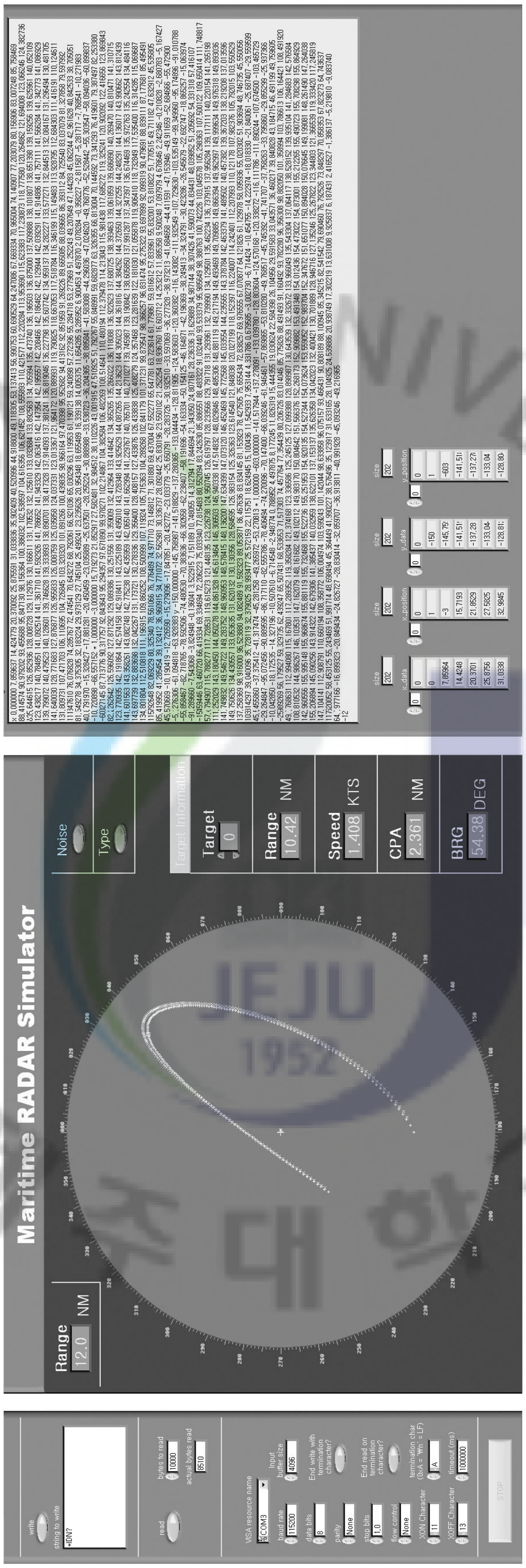

Figure 2-30. The maritime radar simulator

2.5 Conclusion

The SSWT to track moving targets was proposed in this research. The proposed algorithm can effectively track the target by using a piecewise linear model in a non-linear moving target trajectory.

To verify the proposed algorithm, the maritime radar simulator with the SSWT is implemented using a TMS320C6711 digital signal processor (DSP) board and LabVIEW 8.5 and is compared against the α-β tracker and the Kalman tracker.

The proposed algorithm is more effective than the α-β tracker for non-linear moving targets. The computation time for each tracking algorithm running on this board was estimated. It turned out that our algorithm requires much less time than the Kalman tracking algorithm. The proposed tracking algorithm has a couple of advantages over the Kalman tracking algorithm in terms of computation time, and non-requirement of the statistical characteristics of a target.

Our implementation by utilizing the proposed algorithm can improve the tracking performance of the maritime radar.

CHAPTER 3

The Parametric Array Sonar System

3.1 Introduction

The sonar system has an important role in underwater communication. In the underwater communications, transmitted acoustic signal is corrupted by interference from multipath [10]. A parametric array transducer is capable of radiating a narrow beam with very low sidelobe levels [11]. In certain cases, the parametric array transducer can help the multipath problem. To improve the performance of the underwater communications, the statistical signal processing methods will be required.

In the thesis, the sonar communication system using a parametric array transducer was demonstrated. The on-off keying scheme was applied to modulate the signal [19]. For a good communication, the maximum likelihood method using averaged signal for a particular window size is used in the system [12].

The system is composed of a parametric array transducer, a NI PXI system, a microphone, a power amplifier, a PC with DAQCard, and the control software developed by LabVIEW 8.5. The sonar communication system has GUI which allows the user to change the parameter. The GUI can also be easily modified based on the characteristics of a parametric array transducer. The implemented system can effectively evaluate the performance of the parametric array transducer.

Section 3.2 gives a brief overview of the detection algorithm. Section 3.3 presents the implemented transmitter, receiver and the experimental results. Finally, Section 3.4 describes some of the research results.

3.2 Maximum Likelihood Method

The decision rule defined as [12]

$$d(z)=\begin{cases} d_1 & if\ p\left(z|m_1\right)>\left(z|m_2\right) \\ d_2 & if\ p\left(z|m_2\right)>\left(z|m_1\right) \end{cases} \tag{3-1}$$

$$\begin{aligned} &m_1 : z = n \\ &m_2 : z = s+n \end{aligned} \tag{3-2}$$

where the observation of m_1 is the zero-mean unit-variance gaussian random noise, the observation of m_2 is $s+n$, s is the mean value.

The conditional probability density of z given m_1 or m_2 as

$$\begin{aligned} p\left(z|m_1\right) &= \frac{1}{\sqrt{2\pi}}\exp\frac{-z^2}{2} \\ p\left(z|m_2\right) &= \frac{1}{\sqrt{2\pi}}\exp\frac{-(z-s)^2}{2} \end{aligned} \tag{3-3}$$

The decision regions are

$$\begin{aligned} Z_1 &= \left\{z : p\left(z|m_1\right) > p\left(z|m_1\right)\right\} \\ Z_2 &= \left\{z : p\left(z|m_1\right) < p\left(z|m_1\right)\right\} \end{aligned} \tag{3-4}$$

The likelihood ratio $\Lambda\left(z\right)$ defined as

$$\Lambda\left(z\right) = \frac{p\left(z|m_2\right)}{p\left(z|m_1\right)} \tag{3-5}$$

Then Z_1 and Z_2 may be defined as

$$\begin{aligned} Z_1 &= \left\{z : \Lambda\left(z\right) < 1\right\} \\ Z_2 &= \left\{z : \Lambda\left(z\right) > 1\right\} \end{aligned} \tag{3-6}$$

It can be expressed shortly

$$\Lambda(z) \underset{d_1}{\overset{d_2}{\gtrless}} 1 \tag{3-7}$$

Using above the equations, the problem can be solved

$$\begin{aligned}\Lambda(z) &= \frac{p(z|m_2)}{p(z|m_1)} = \frac{\left(1/\sqrt{2\pi}\right)\exp\left[-(z-s)^2/2\right]}{\left(1/\sqrt{2\pi}\right)\exp\left[-z^2/2\right]} \\ &= \exp\frac{-\left[(z-s)^2 - z^2\right]}{2} \\ &= \exp\frac{(2z-s)}{2}\end{aligned} \tag{3-8}$$

The decision rule can be written as

$$\exp\frac{(2z-s)}{2} \underset{d_1}{\overset{d_2}{\gtrless}} 1 \tag{3-9}$$

Take the natural logarithm of (3-9)

$$\frac{2z-s}{2} \underset{d_1}{\overset{d_2}{\gtrless}} 0 \tag{3-10}$$

Then (3-11) is obtained

$$z \underset{d_1}{\overset{d_2}{\gtrless}} \frac{s}{2} \tag{3-11}$$

and the decision regions can be defined as

$$\begin{aligned}Z_1 &= \left\{z : z < \frac{s}{2}\right\} = \left(-\infty, \frac{s}{2}\right) \\ Z_2 &= \left\{z : z > \frac{s}{2}\right\} = \left(\frac{s}{2}, \infty\right)\end{aligned} \tag{3-12}$$

Fig. 3-1 illustrates the signal that is obtained by the experiment. The experiment setup is explained in section 3.3.

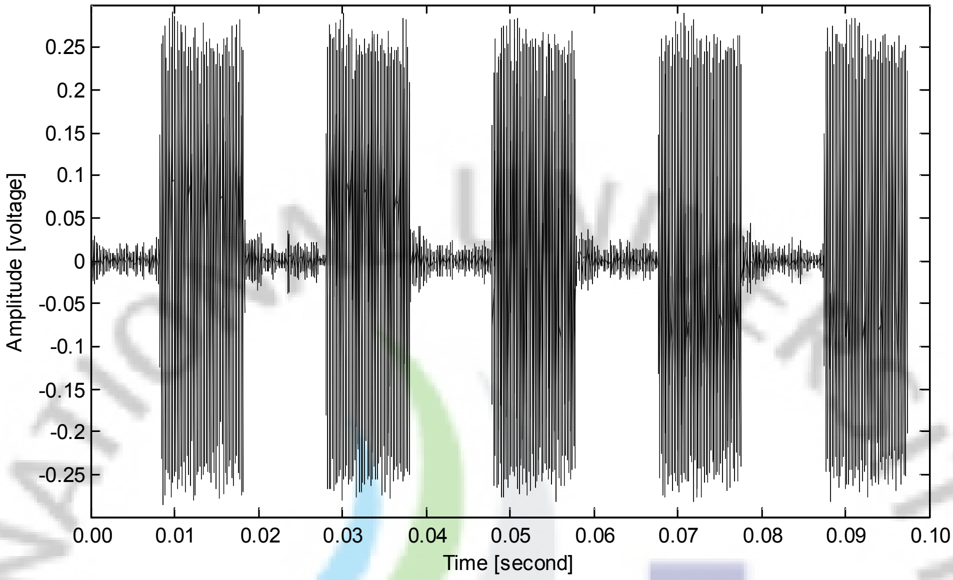

Figure 3-1. Measured signal

To detect the signal, averaging technique was applied, additionally. The averaged signal is obtained by

$$\begin{aligned} m_1 : z &= \frac{1}{N}\sum_{i=1}^{N}\left|s_{1i}+n_{1i}\right| \\ m_2 : z &= \frac{1}{N}\sum_{i=1}^{N}\left|s_{2i}+n_{2i}\right| \end{aligned} \qquad (3\text{-}13)$$

where N is the sample number.

The average value of the signal as shown in Fig. 3-2 is obtained based on (3-13).

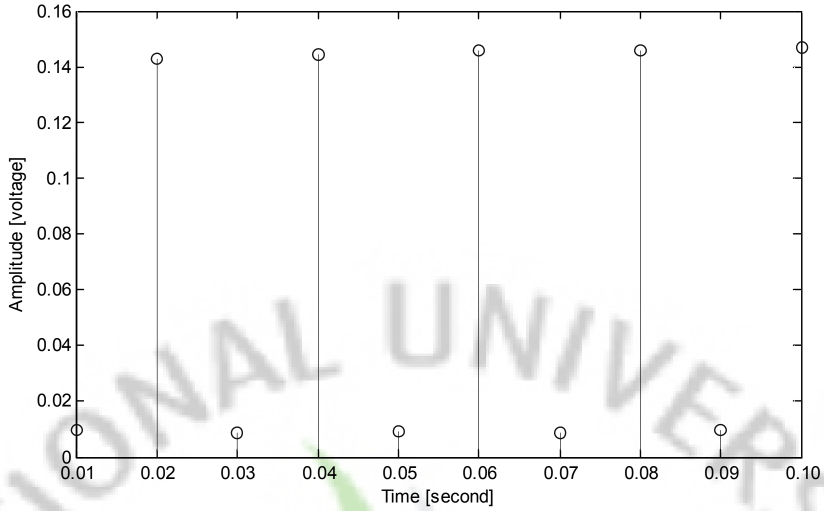

Figure 3-2. The average value of the signal

As shown in Fig. 3-2, the signal is absolute and averaged. Fig. 3-3 illustrates the probability density function of the averaged signal. The averaged value of the signal has Gaussian distribution.

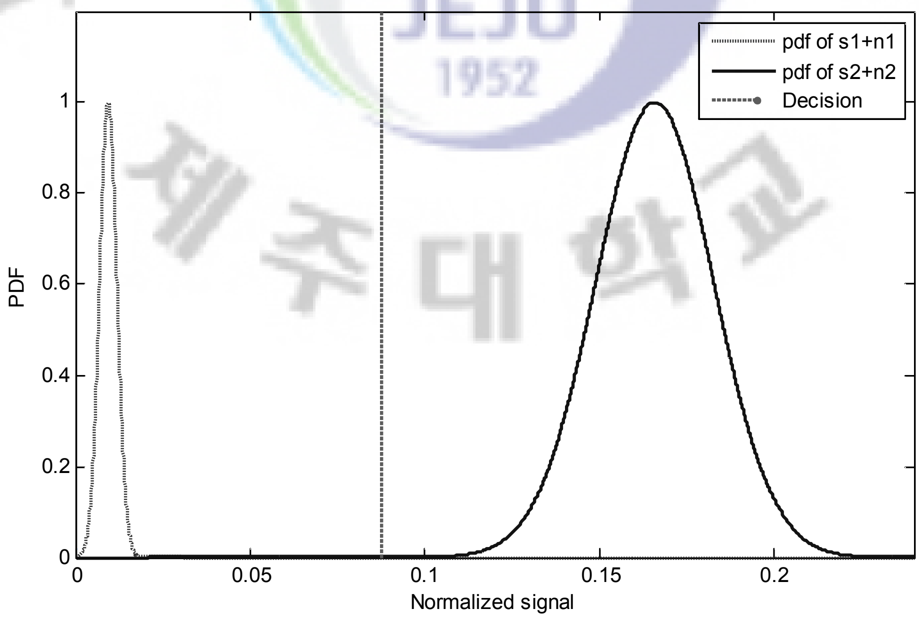

Figure 3-3. The probability density function of the signal

The decision rule from the ML method is

$$z \underset{d_1}{\overset{d_2}{\gtrless}} \frac{(s_2 + s_1)}{2} \tag{3-13}$$

where s_1 and s_2 are mean values.

The standard deviations of $s_1 + n_1$ and $s_2 + n_2$ are 0.0025 and 0.0169, respectively. The means of $s_1 + n_1$ and $s_2 + n_2$ are 0.0094 and 0.1658, respectively. Hence, if $z > 0.0876$, we decide d_2 and if $z < 0.0876$, we decide d_1.

3.3 Implemented System

3.3.1 Transmitter

The parametric array sonar system consists mainly of transmitter and receiver. The block diagram of the transmitter is shown in Fig. 3-4 [20].

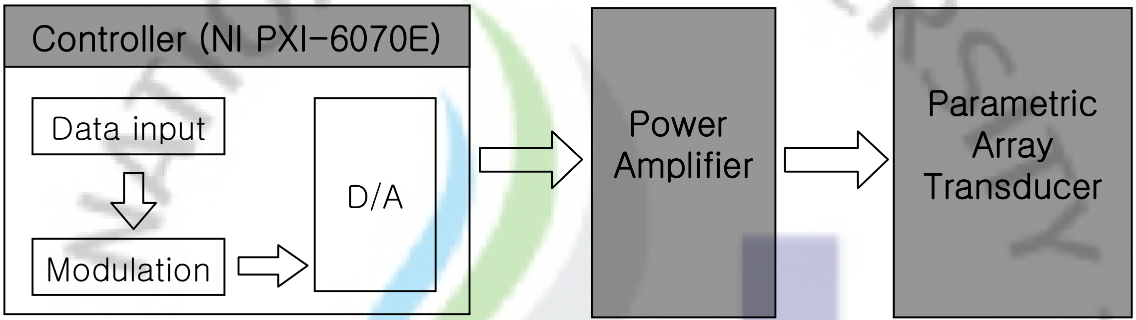

Figure 3-4. Block diagram of transmitter

The transmitter is composed of a parametric array transducer, a NI PXI system and a power amplifier. The PXI system plays a role in the modulation and the digital to analog conversion (DAC). The control software is programmed by LabVIEW 8.5. A brief overview of the NI PXI system is shown in Table 3-1.

Table 3-1. Specifications of PXI-6070E

Item	Description	
Output Resolution	12 bits	
Output Rate	1 MS/s	
Output Range	±10 V	
FIFO Buffer Size	2,048 samples	

The prototype parametric array transducer is developed by vibration/acoustics and transducers laboratory of Pohang University of Science and Technology [21]. Fig. 3-5 shows the structure of the prototype parametric array transducer.

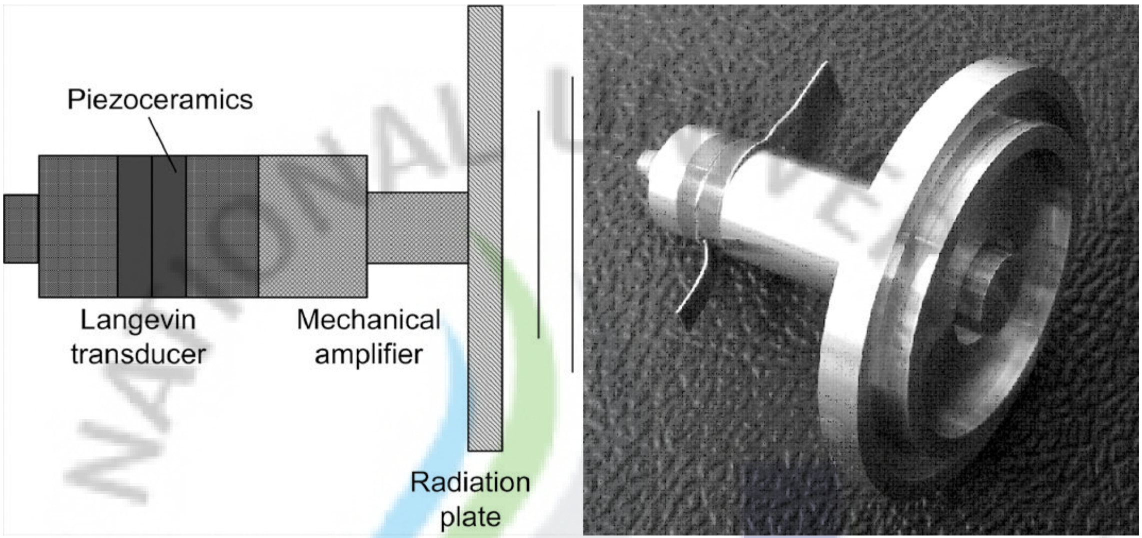

Figure 3-5. Structure of the prototype parametric array transducer

The prototype parametric array transducer has 82 kHz and 122 kHz resonance frequencies, and its size is 50mm x 50mm.

3.3.2 Receiver

The block diagram of the receiver is shown in Fig. 3-6. The receiver is composed of a microphone, power amplifier and a PC with DAQCard. The transmitted signal has 40 kHz difference frequency because of the parametric array transducer characteristic [22]. The received signal is amplified through a power amplifier. In the PC, signal is sampled, filtered and demodulated. To remove the sampling noise, band-pass filter (38 kHz, 42 kHz) is used [23].

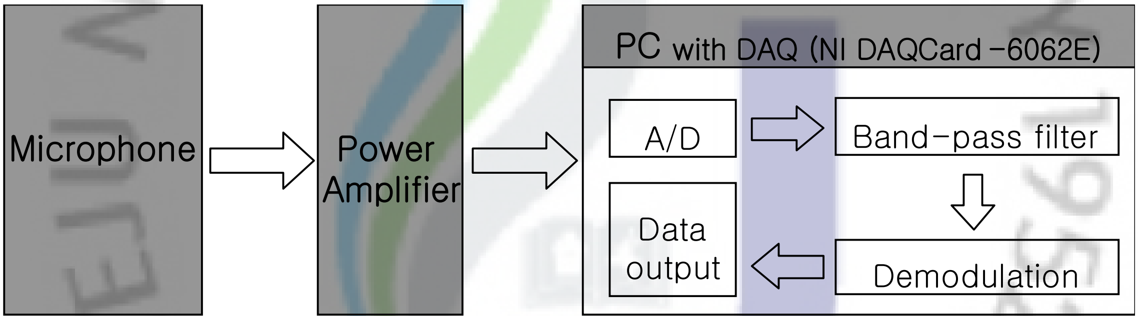

Figure 3-6. Block diagram of receiver

A brief overview of the NI PXI system is shown in Table 3-2.

Table 3-2. Specifications of DAQCard-6062E

Item	Description	
Input Resolution	12 bits	
Output Rate	500 kS/s	
Input Range	±0.05 to ±10 V	
FIFO Buffer Size	2,048 samples	

3.3.3 Experimental Result.

A simple communication experiment has been carried out in the air [24]. The signal was generated by on-off keying modulation scheme. The primary frequencies are 42 kHz and 82 kHz, respectively. The signal frame consists of 20 bits flag and 130 bits data as shown in Fig. 3-7 and it was sent repeatedly [25].

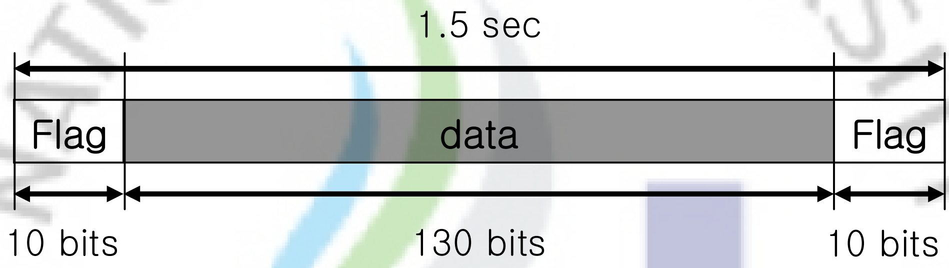

Figure 3-7. The structure of the signal frame

Fig. 3-8 illustrates the generated signal after ADC at the transmitter which is measured by an oscilloscope. Fig. 3-8 (a) shows the form of the modulated signal, and Fig. 3-8 (b) shows a period of the frame.

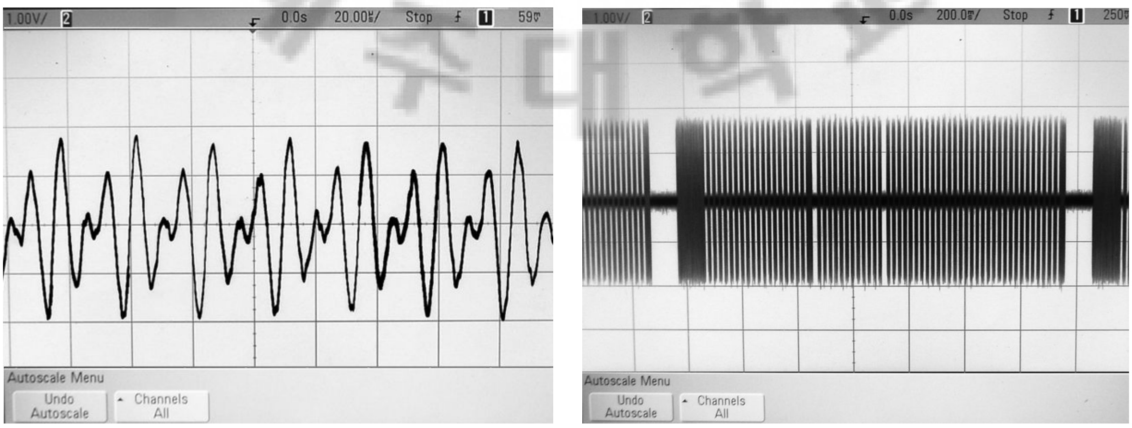

Figure 3-8. (a) The modulated signal and (b) a period of frame measured by oscilloscope

Fig. 3-9 illustrates the software to control the transmitter of the sonar system.

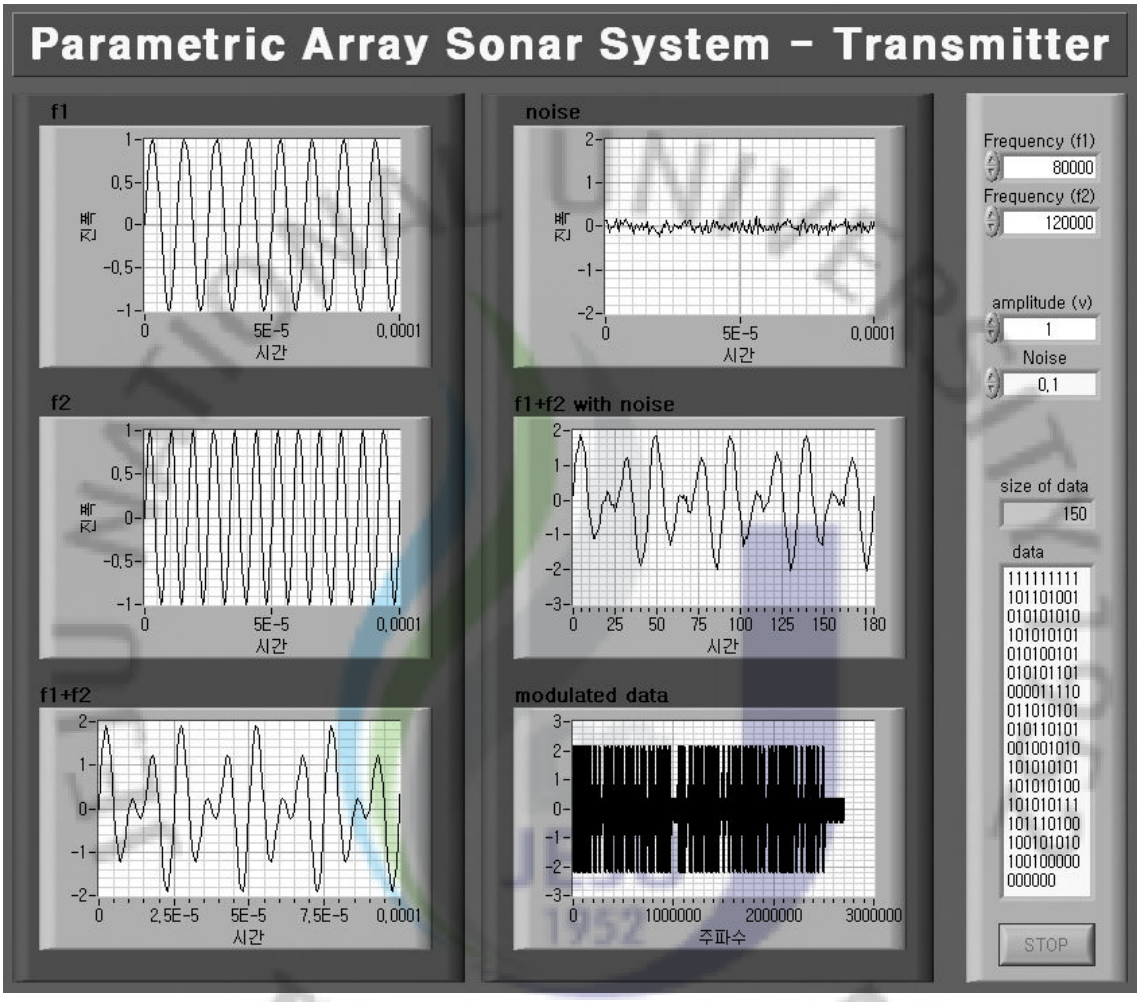

Figure 3-9. The GUI transmitter

As shown in Fig. 3-9, the control software has GUI which allows the user to change the parameter. The user can control primary frequencies, the output voltage, the input data and an additional noise. An additional noise is useful in case of simulation for an arbitrary channel.

Fig. 3-10 illustrates the receiver of the parametric array sonar system.

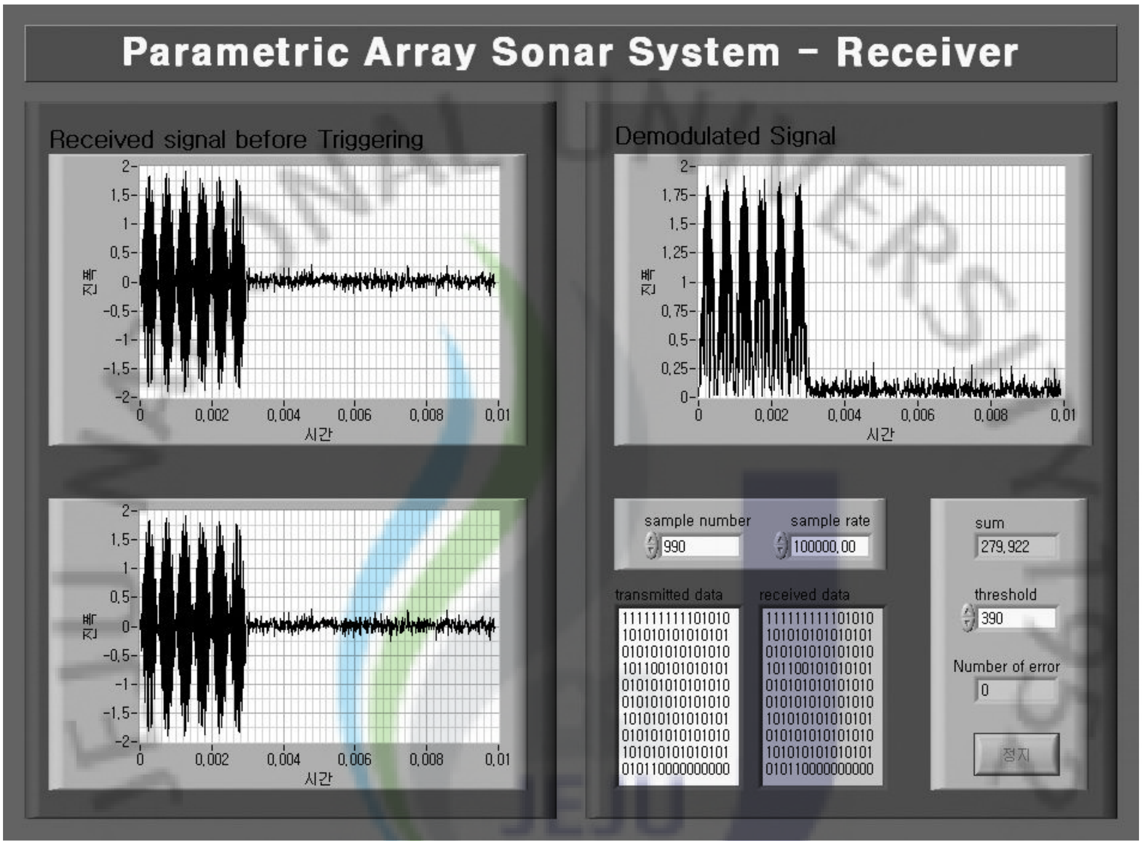

Figure 3-10. The GUI receiver

As shown in Fig. 3-10, the receiver controller is designed to change the sample number, the sample rate and the detection level. To detect the signal, the measured signal was averaged for a particular window size before applying the maximum likelihood method. The window size is same as the sampling number as shown in Fig. 3-10.

3.4 Conclusion

The maximum likelihood method using averaged signal for a particular window size was presented. The proposed algorithm can quickly and exactly detect the signal without error.

To verify the algorithm, the sonar communication system is implemented. The system is composed of the control software, a parametric array transducer, a NI PXI system, a microphone, a power amplifier and a PC with DAQCard.

The control software is easy to modify the program for the characteristic of the prototype parametric array transducer by utilizing LabVIEW 8.5. The implemented system can effectively evaluate the performance of the parametric array transducer.

Our implementations will be helpful to develop a sonar communication system using the parametric array transducer.

CHAPTER 4
Conclusion Remarks

The statistical signal processing algorithms were proposed. The thesis covers two major implementations using these algorithms: 1) The maritime radar simulator, 2) The parametric array sonar system.

For the maritime radar simulator, the SSWT was proposed to track moving targets. To verify the proposed algorithm, the GUI maritime radar simulator with the SSWT is implemented using a TMS320C6711 digital signal processor (DSP) board and LabVIEW 8.5. The simulator is compared against the α-β tracker and the Kalman tracker. The proposed algorithm can effectively track the non-linear moving target by using a piecewise linear model in a target trajectory, which has better performance than the α-β tracker for non-linear moving targets. The computation time for each tracking algorithm running on the DSP board was measured. It turned out that our algorithm requires much less time than the Kalman tracking algorithm. The proposed tracking algorithm has advantages compared with the Kalman tracking algorithm in terms of calculation time, and our algorithm does not require prior statistical characteristics of a target.

For the parametric array sonar system, the maximum likelihood method using averaged signal for a particular window size was presented. The algorithm can quickly and exactly detect the signal without error. For the underwater communication, the sonar system with the proposed algorithm is developed using a prototype parametric array transducer. The system is composed of the control software, a parametric array transducer, a NI PXI system, a microphone, a power amplifier and a PC with DAQCard. The control software designed by LabVIEW 8.5, could be modified easily, according to different parametric array transducers. The implemented system can effectively evaluate the performance of the parametric array transducer

Our results show that the maritime radar simulator and the parametric array sonar system could be potential approaches to improve the performance of ocean equipments.

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SUMMARY (in KOREAN)

해양 레이더와 소나 시스템은 항해와 충돌 방지, 해양 탐사, 통신과 같은 중요한 역할에 사용된다. 이러한 장비들은 무엇보다 정확성과 신뢰성이 요구되며, 그 성능을 향상시키기 위해 다양한 통계적 신호처리 기법들이 사용되고 있다. 본 논문에서는 기존의 통계적 신호처리 기법들과 새로운 추적 기법을 소개하고, 검증을 위한 해양 레이더 시뮬레이터와 파라메트릭 배열 소나 시스템을 구현하였다.

해양 레이더를 위한 추정 기법은 일반적으로 α-β 필터, 칼만 필터 등이 사용되고 있다. α-β 필터는 구조가 간단하고 계산량이 적지만, α, β 계수가 적절치 않거나 물체가 급격하게 이동할 경우 큰 추정 오차가 발생하는 단점을 갖는다. 칼만 필터는 추적하려는 물체의 통계적 특성에 대한 정보를 요구하며, 계산량이 많은 단점을 지니고 있다. 이와 같은 문제들을 해결하기 위하여 본 논문에서는 새로운 추적 기법인 Switched Slide Window Tracker를 제안하였다. 제안된 기법은 부분 선형화를 적용한 슬라이딩 윈도우를 이용하여 물체를 추적하는 기법으로 물체의 급격한 변동에 대해서 α-β 필터보다 정확한 성능을 보였으며, 칼만 필터에 비해 계산량이 적고 추적하려는 물체의 통계적 특성에 대한 정보 없이도 우수한 추적 성능을 보임을 입증하였다.

수중에서의 다중 경로 특성은 수중 통신을 수행하는데 있어 열악한 환경을 제공한다. 파라메트릭 배열 트랜스듀서는 고 지향성을 가지며, 그로 인해 다중 경로의

영향을 최소화 시키는 것이 가능하다. 본 논문은 파라메트릭 배열 트랜스듀서를 이용한 소나 시스템을 구현하였으며, 신호를 검파하기 위하여 평균화시킨 수신 신호에 대하여 최대우도법(Maximum likelihood method)을 적용하였다.

제안된 추적기법의 검증으로 α-β 필터와 칼만 필터, 그리고 새롭게 제안한 Switched slide window tracker를 DSP 보드에 구현하여 각각의 성능을 비교하였으며, 랩뷰 소프트웨어를 사용하여 GUI 해양 레이더 시뮬레이터를 구현하였다. 검파 기법의 검증으로는 고 지향 특성을 갖는 파라메트릭 배열 트랜스듀서와 NI PXI 장비를 이용하여 소나 시스템을 구현하고 ML 기법을 적용하여 수신 성능을 향상시켰다.

본 논문에서 구현된 결과는 실제 해양 장비의 개발에 소요되는 비용과 시간을 감소시키고, 성능을 향상시키는데 적용될 수 있다. 또한 제안된 알고리즘은 레이더 및 소나 시스템뿐만 아니라 통계학적 신호처리가 필요한 다양한 분야에 적용될 수 있다.

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