

Research Article

Ship-Borne Phased Array Radar Using GA Based Adaptive α - β - γ Filter for Beamforming Compensation and Air Target Tracking

J. Mar,^{1,2} Chen-Chih Liu,¹ and M. B. Basnet¹

¹Department of Communications Engineering, Yuan-Ze University, 135 Yuan-Tung Road, Jungli, Taoyuan 320, Taiwan

²Communication Research Center, Yuan-Ze University, 135 Yuan-Tung Road, Jungli, Taoyuan 320, Taiwan

Correspondence should be addressed to J. Mar; eejmar@saturn.yzu.edu.tw

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Beam pointing error caused by ship motion over the ocean affects the tracking performance of the ship-borne phased array radar. Due to the dynamic nature of the sea environments, the ship-borne phased array radar must be able to compensate for the ship's motion adaptively. In this paper, the adaptive α - β - γ filter is proposed for the ship-borne phased array radar to compensate for the beam pointing error and to track the air target. The genetic algorithm (GA) and the particle swarm optimization (PSO) methods are applied to estimate the gain parameters of adaptive α - β - γ filters, while achieving the optimum objective of minimum root mean square error (RMSE). The roll and pitch data measured from a gyroscope of the sea vehicle and generated from ship motion mathematical model are used in the experiments. The tracking accuracy of adaptive α - β - γ filter using the GA method is compared with PSO method under different ship motion conditions. The convergent time and tracking accuracy of ship-borne phased array radar using the proposed GA based adaptive α - β - γ filter are also compared with the adaptive extended Kalman filter (AEKF). Finally, it is proved that the proposed GA based adaptive α - β - γ filter is a real time applicable algorithm for ship-borne phased array radar.

1. Introduction

Sea wave causes the effect of roll and pitch motions on ships. These ship rotational motions result in measurement error in phased array radar aboard the ship. The antenna stabilization to achieve the beam pointing accuracy over the long dwell time is an important issue for ship-borne phased array radar [1]. There are two ship motion compensations: compensation for rotational motion (i.e., pitch, roll, and heading angle) and compensation for translational motion (i.e., radial speed relative to the earth). Gyroscope provides pitch, roll, heading angles of the ship, speed, course, and vertical velocity of antenna installed on the ship at a data rate of 10 Hz. To compensate for the translational motion, the speed, course, and vertical velocity acquired from the gyroscope are averaged for the duration of radar-dwell time. Then the Doppler shift introduced by the translational motion is estimated in the digital signal processor (DSP) of the radar to compensate the radial velocity. The radar

control computer (RCC) provides the target locations relative to earth, schedules beam directions, and predicts beam pointing error to the beam steering controller (BSC), which compensates for the beam pointing error and controls the phased array antenna to point the beam at the target direction relative to the ship coordinates.

The motion compensation method based on coordinate conversion has been described in [2, 3], which requires the measurement of a device's coordinates, the ship's coordinates, and the earth's coordinates systems to compensate the device errors due to motion disturbances. In [1], Kalman filtering along with coordinates conversion is applied to reduce the beam pointing error and to stabilize a tracking beam. The α - β - γ filter, which is more easily implemented than a generalized Kalman filter, is used for motion compensation under different sea states in [1]. The sea environments are very dynamic; hence, there is need of an adaptive system for controlling and compensating devices regardless of ship motion. Most recent works have used Kalman filtering (KF) [4]

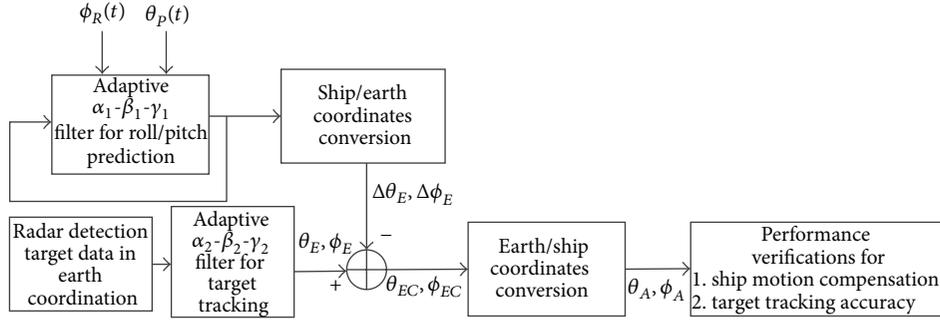


FIGURE 1: High level structure of ship rotational motion compensation for phased array radar.

and extended Kalman filtering (EKF) [5] to estimate the ship's attitude. Estimation accuracy of KF and EKF depends on the values of different parameters, such as error covariance matrices; thus, the KF and EKF require knowledge of covariance. In [6], the automatic beam pointing error compensation mechanism employs the parallel fuzzy basis function network (FBFN) architecture to estimate the beam pointing error caused by roll and pitch of the ship. The effect of automatic beam pointing error compensation mechanism on the tracking performance of adaptive extended Kalman filter (AEKF) implemented in ship-borne phased array radar is investigated. It shows that the tracking error of AEKF converges to less than about 20 m at 550 iterations (sec/iteration) and the estimation error will remain within the range of about 20 m when beam pointing error is compensated by FBFN controller.

The α - β - γ filter has a similar structure with the KF but depends on the gain value of α , β , and γ which are limited and interdependent [7–9]. The uses of various methods to adjust parameter values for Kalman filter, EKF, and α - β - γ filter have been proposed and implemented over the years. Fuzzy membership function is used in [10] to estimate and correct the target position for the signal being tracked. Genetic algorithm (GA) is used in [9] to search the suitable parameter values for the α - β - γ filter, which can provide the approximate position, velocity, and acceleration signal and simultaneously decrease the measurement noise. Particle swarm optimization (PSO) is used in [11] to tune the noise covariance of a Kalman filter. In [12], the PSO is used to find the optimal gain parameter values for an α - β - γ filter. PSO and GA methods are suitable for the real time application because they do not require differentiation and are less complicated than other methods.

In this paper, GA based adaptive α - β - γ filter is proposed for automatic beam pointing error correction and air target tracking in three-dimensional space. Continuous monitoring of the environment and adapting filter gain parameter with less computational burden is needed for real time application. The adaptive α - β - γ filter requires knowledge of the coefficients for which GA algorithm is used only in certain time intervals. GA is used to find the gain values by minimizing the objective function, that is, root mean square error (RMSE). The proposed adaptive α - β - γ filter algorithm

is implemented and compared with using PSO method. The roll and pitch data were recorded by a gyroscope of the sea vehicle to simulate the tracking performance of ship-borne phased array radar using the proposed adaptive α - β - γ filter. In addition, the roll and pitch data generated from ship motion mathematical model at sea states 2 and 3 are also applied for the proposed adaptive α - β - γ filter to verify the correctness of the test results.

The rest of this paper is organized as follows: the model of ship rotational motion, coordinates transform, and planar array antenna of ship-borne phased array radar are described in detail in Section 2. The algorithm of the proposed adaptive α - β - γ filter based on the GA is presented in Section 3, where the α - β - γ filter, GA gain estimator, PSO gain estimator, and optimization problem formulation are described. In Section 4, six different experimental cases are performed; the variations of roll and pitch angles in sea states 2 and 3 are analyzed; the GA and PSO methods are used to determine the optimal filter gain of adaptive α - β - γ filter that minimizes RMSE; the tracking performance of ship-borne phased array radar using the proposed adaptive α - β - γ filter is simulated. Finally, conclusions are made in Section 5.

2. Ship Rotational Motion Compensation

The ship-borne phased array radar must be able to compensate the ship's motion and track the maneuvering targets automatically. The adaptive α - β - γ filtering algorithm is designed to real time compensate the errors caused by the ship's motion. The block diagram of rotational motion compensation system for ship-borne phased array radar is shown in Figure 1, which consists of adaptive α - β - γ filter for beam pointing error prediction, ship coordinates/earth coordinates conversion, earth coordinates/ship coordinates conversion, and adaptive α - β - γ filter for target tracking. The roll angle $\phi_R(t)$ and the pitch angle $\theta_p(t)$ of the ship angular motion are measured by the gyroscope. (θ_A, ϕ_A) is the antenna beam pointing angle relative to the ship body, where θ_A is the angle off antenna boresight, and ϕ_A is the azimuth angle counterclockwise from the bow of the ship. Assume that the beam steering angle at a certain time instant is (θ_0, ϕ_0) , the antenna point angle offset caused by the ship motion (pitch,

TABLE 1: Sea state parameters.

	Roll		Pitch	
	A_R (°)	T_R (sec)	A_P (°)	T_P (sec)
Sea state 2	1	2.5	0.2	1.2
Sea state 3	1	2.0	0.2	0.6

roll) is (θ_e, ϕ_e) , and then the current antenna pointing angle is (θ_E, ϕ_E) with respect to the earth coordinates:

$$\theta_E = \theta_0 + \theta_e, \quad \phi_E = \phi_0 + \phi_e. \quad (1)$$

If the beam pointing error is predicted as $(\Delta\theta_E, \Delta\phi_E)$, then the beam pointing angle is corrected as

$$\theta_{EC} = \theta_0 + \theta_e - \Delta\theta_E, \quad \phi_{EC} = \phi_0 + \phi_e - \Delta\phi_E. \quad (2)$$

The value of (θ_{EC}, ϕ_{EC}) is approximate to (θ_0, ϕ_0) .

2.1. Ship Rotational Motion Model. Ship is affected by the waves in the ocean, resulting in six degrees of freedom of movement. In this paper, assuming zero yaw angle, the simplified roll and pitch model [1, 13] is adopted to describe the ship rotational motion in the earth coordinates. Ship's rotational motion is modeled with sinusoidal signal. The roll angle is

$$\phi_R(t) = A_R \sin(\omega_R t) + n_R(t). \quad (3)$$

The pitch angle is

$$\phi_P(t) = A_P \sin(\omega_P t) + n_P(t), \quad (4)$$

where A_R and A_P are the amplitude of ship's roll and pitch angles, $n_R(t)$ and $n_P(t)$ are assumed to be zero mean Gaussian noise, T_R and T_P are the roll and pitch periods, and $\omega_R = 2\pi/T_R$ and $\omega_P = 2\pi/T_P$ are the roll and pitch angular frequencies.

The random roll and pitch angle errors caused by other unknown factors, including the change of ship's traveling direction and weather, in the actual ship navigation environment will be considered into the standard deviation of the noise terms. The amplitude and period parameters of sea states 2 and 3 are listed in Table 1 [1].

2.2. Coordinates Transform. Since the phased array antenna is installed on the ship, the beam steering control employs the ship body coordinates. But the target tracking of adaptive α - β - γ filter employs the Earth coordinates. The Euler coordinates transform formula is used to convert antenna beam pointing angle relative to the earth (θ_E, ϕ_E) , where θ_E is the angle from vertical and ϕ_E is the angle clockwise from true north, into antenna beam pointing angle relative to the ship body (θ_A, ϕ_A) [13]:

$$\begin{bmatrix} \sin \theta_A \cos \phi_A \\ \sin \theta_A \sin \phi_A \\ \cos \theta_A \end{bmatrix} = T(\phi) T(\theta) T(\psi) \begin{bmatrix} \sin \theta_E \cos \phi_E \\ -\sin \theta_E \sin \phi_E \\ \cos \theta_E \end{bmatrix}, \quad (5)$$

where the coordinates transform matrices are defined as

$$\begin{aligned} T(\phi) &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \phi & \sin \phi \\ 0 & -\sin \phi & \cos \phi \end{bmatrix}, \\ T(\theta) &= \begin{bmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{bmatrix}, \\ T(\psi) &= \begin{bmatrix} \cos \psi & -\sin \psi & 0 \\ \sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix}, \end{aligned} \quad (6)$$

where the ship roll angle ϕ is positive with downward roll of starboard, the ship pitch angle θ is positive with bow pitch upward, and the ship yaw angle ψ is positive clockwise from the north.

2.3. Planar Array Antenna. An $M \times N$ element planar array [6] is designed for the ship-borne phased array radar system, which includes the beamforming (BF) mode and direction of arrival (DOA) mode. The planar array can produce multibeam in the azimuth and elevation by using the beamformer network (BFN), which consists of a set of power dividers and phase shifters. The planar array using amplitude comparison method [14] generates the difference signal patterns for the DOA estimation. The difference signals obtained from two neighboring beams can measure the DOA of the target signal of the ship-borne phased array radar system. The beam pattern is expressed as [14, 15]

$$\begin{aligned} AF(\theta, \phi) &= \sum_{n=1}^N I_{1n} \left[\sum_{m=1}^M I_{m1} e^{j(m-1)(kd_x \sin \theta \cos \phi + \beta_x)} \right] \\ &\quad \times e^{j(n-1)(kd_y \sin \theta \sin \phi + \beta_y)} = S_{xm} S_{ym}, \end{aligned} \quad (7)$$

where

$$\begin{aligned} S_{xm} &= \sum_{m=1}^M I_{m1} e^{j(m-1)(kd_x \sin \theta \cos \phi + \beta_x)}, \\ S_{ym} &= \sum_{n=1}^N I_{1n} e^{j(n-1)(kd_y \sin \theta \sin \phi + \beta_y)}, \\ \beta_x &= -kd_x \sin \theta_t \cos \phi_t, \\ \beta_y &= -kd_y \sin \theta_t \sin \phi_t, \end{aligned} \quad (8)$$

where $I_{m1} = I_{1n} =$ Chebyshev weighting [13], $M =$ the number of array elements in the x -axis, $N =$ the number of array elements in y -axis, $\phi_t =$ the azimuth steering angle of the main beam, $\theta_t =$ the elevation steering angle of the main beam, $d_x =$ the interelement spacing in x -axis, $d_y =$ the interelement spacing in y -axis, $k = 2\pi/\lambda =$ the phase propagation constant, and λ is the wavelength of the carrier.

The phase of the RF signal at each array element is adjusted to steer the beam to the coordinates (θ_t, ϕ_t) .

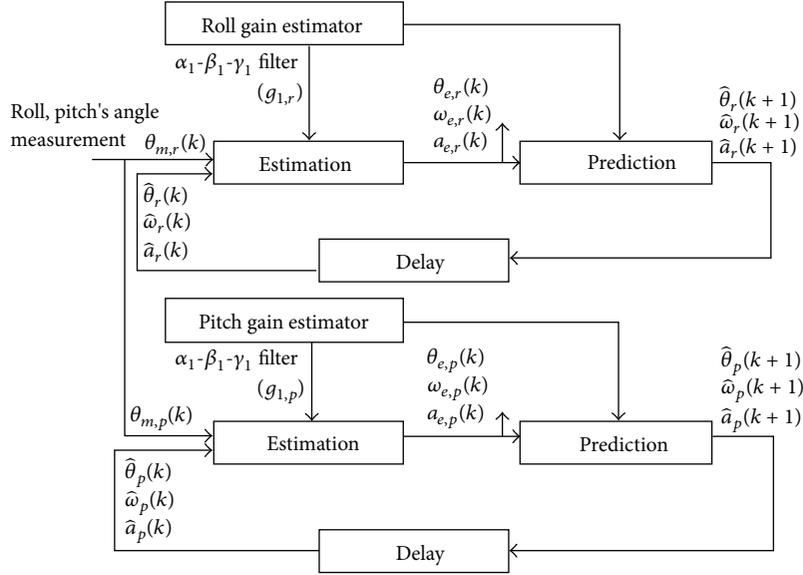


FIGURE 2: Parallel adaptive α - β - γ filter for beam pointing error prediction.

3. Adaptive α - β - γ Filter

As shown in Figure 1, the adaptive α - β - γ filters are applied to beam pointing error prediction and target tracking, respectively.

3.1. Parallel Adaptive α - β - γ Filter for Beam Pointing Error Prediction. Figure 2 shows the beam pointing error prediction system, which consists of separate adaptive α_1 - β_1 - γ_1 filters to predict the roll and pitch angles of ship motion and their outputs are fed into the beam steering controller (BSC). The BSC compensates the beam pointing errors of the phased array antenna onboard the ship to reduce the impact of the roll and pitch motion on the phased array radar. Roll and pitch data are random but they are similar in nature and they can be characterized with different amplitudes and frequencies [1]. The α_1 - β_1 - γ_1 filter predicts the next positions using current error also known as innovation [8]. This innovation process has two steps: prediction and estimation.

The pitch prediction equations are expressed as

$$\begin{aligned}\hat{\theta}_p(k+1) &= \theta_{e,p}(k) + T_1 \omega_{e,p}(k) + \frac{T_1^2}{2} a_{e,p}(k), \\ \hat{\omega}_p(k+1) &= \omega_{e,p}(k) + T_1 a_{e,p}(k), \\ \hat{a}_p(k+1) &= a_{e,p}(k).\end{aligned}\quad (9)$$

The pitch estimation equations are expressed as

$$\begin{aligned}\theta_{e,p}(k) &= \hat{\theta}_p(k) + \alpha_{1,p} [\theta_{m,p}(k) - \hat{\theta}_p(k)] + n_{1,p}(k), \\ \omega_{e,p}(k) &= \hat{\omega}_p(k) + \frac{\beta_{1,p}}{T_1} [\theta_{m,p}(k) - \hat{\theta}_p(k)], \\ a_{e,p}(k) &= \hat{a}_p(k) + \frac{\gamma_{1,p}}{2T_1^2} [\theta_{m,p}(k) - \hat{\theta}_p(k)],\end{aligned}\quad (10)$$

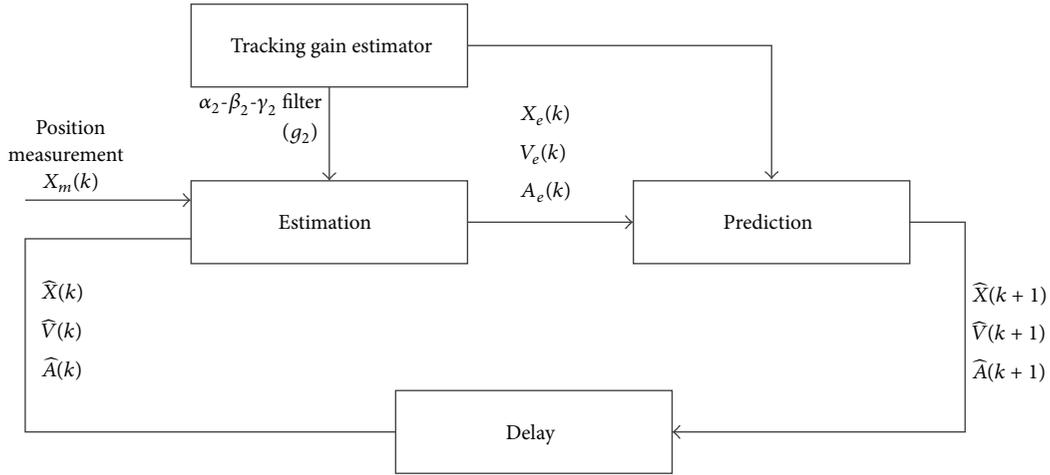
where $\hat{\theta}_p(k+1)$, $\hat{\omega}_p(k+1)$, and $\hat{a}_p(k+1)$ are pitch angular position, pitch angular velocity, and pitch angular acceleration values predicted at $(k+1)$ th interval, respectively. The sampling time $T_1 = 0.1$ sec, $\theta_{e,p}(k)$, $\omega_{e,p}(k)$, and $a_{e,p}(k)$ are pitch angular position, pitch angular velocity, and pitch angular acceleration estimated at k th interval. $\alpha_{1,p}$, $\beta_{1,p}$, and $\gamma_{1,p}$ are the smoothing parameters whose region of stability and parameter constraint have been studied in [8]. The relationship among $\alpha_{1,p}$, $\beta_{1,p}$, and $\gamma_{1,p}$ parameters can be related to pitch gain $g_{1,p}$, where $0 < g_{1,p} < 1$. The formula is described as follows:

$$\begin{aligned}\alpha_{1,p} &= 1 - g_{1,p}^3, \\ \beta_{1,p} &= 1.5 \cdot (1 + g_{1,p}) (1 - g_{1,p})^2, \\ \gamma_{1,p} &= (1 - g_{1,p})^3.\end{aligned}\quad (11)$$

The roll prediction equations, roll estimation equations, and roll smoothing parameters have similar forms as the pitch prediction equations, pitch estimation equations, and pitch smoothing parameters, respectively.

3.2. Adaptive α - β - γ Filter for Target Tracking in Three-Dimensional Space. The GA based α_2 - β_2 - γ_2 filter algorithm for target tracking is used by ship-borne phased array radar to predict the next target positions using current error and further improves its tracking accuracy. The tracking process of α_2 - β_2 - γ_2 filter is shown in Figure 3, where the prediction equations are

$$\begin{aligned}\hat{\mathbf{X}}(k+1) &= \mathbf{X}_e(k) + T_2 \mathbf{V}_e(k) + \frac{T_2^2}{2} \mathbf{A}_e(k), \\ \hat{\mathbf{V}}(k+1) &= \mathbf{V}_e(k) + T_2 \mathbf{A}_e(k), \\ \hat{\mathbf{A}}(k+1) &= \mathbf{A}_e(k).\end{aligned}\quad (12)$$

FIGURE 3: Adaptive α - β - γ filter for target tracking in three-dimensional space.

The estimation equations are

$$\begin{aligned} \mathbf{X}_e(k) &= \widehat{\mathbf{X}}(k) + \boldsymbol{\alpha}_2 [\mathbf{X}_m(k) - \widehat{\mathbf{X}}(k)] + \mathbf{n}_2(k), \\ \mathbf{V}_e(k) &= \widehat{\mathbf{V}}(k) + \frac{\boldsymbol{\beta}_2}{T_2} [\mathbf{X}_m(k) - \widehat{\mathbf{X}}(k)], \\ \mathbf{A}_e(k) &= \widehat{\mathbf{A}}(k) + \frac{\boldsymbol{\gamma}_2}{2T_2^2} [\mathbf{X}_m(k) - \widehat{\mathbf{X}}(k)], \end{aligned} \quad (13)$$

where $\mathbf{X}(k) = [x(k), y(k), z(k)]^T$, $\mathbf{V}(k) = [v_x(k), v_y(k), v_z(k)]^T$, and $\mathbf{A}(k) = [a_x(k), a_y(k), a_z(k)]^T$ are the position vector, velocity vector, and acceleration vector, respectively, at time instant k ; $\mathbf{n}_2(k)$ is the zero mean white Gaussian noise and the sampling time $T_2 = 1$ sec. The relationship among $\boldsymbol{\alpha}_2$, $\boldsymbol{\beta}_2$, and $\boldsymbol{\gamma}_2$ parameters can be related to gain factor vector $\mathbf{g}_2 = [g_2, g_2, g_2]^T$. The formula is described as follows:

$$\begin{aligned} \boldsymbol{\alpha}_2 &= \begin{bmatrix} \alpha_{2,x} & 0 & 0 \\ 0 & \alpha_{2,y} & 0 \\ 0 & 0 & \alpha_{2,z} \end{bmatrix} = \begin{bmatrix} 1 - g_2^3 & 0 & 0 \\ 0 & 1 - g_2^3 & 0 \\ 0 & 0 & 1 - g_2^3 \end{bmatrix}, \\ \boldsymbol{\beta}_2 &= \begin{bmatrix} \beta_{2,x} & 0 & 0 \\ 0 & \beta_{2,y} & 0 \\ 0 & 0 & \beta_{2,z} \end{bmatrix} = \begin{bmatrix} 1.5(1 + g_2)(1 - g_2)^2 & 0 & 0 \\ 0 & 1.5(1 + g_2)(1 - g_2)^2 & 0 \\ 0 & 0 & 1.5(1 + g_2)(1 - g_2)^2 \end{bmatrix}, \\ \boldsymbol{\gamma}_2 &= \begin{bmatrix} \gamma_{2,x} & 0 & 0 \\ 0 & \gamma_{2,y} & 0 \\ 0 & 0 & \gamma_{2,z} \end{bmatrix} = \begin{bmatrix} (1 - g_2)^3 & 0 & 0 \\ 0 & (1 - g_2)^3 & 0 \\ 0 & 0 & (1 - g_2)^3 \end{bmatrix}. \end{aligned} \quad (14)$$

3.3. GA Gain Estimator. The flow chart of GA roll/pitch gain estimators of adaptive α - β - γ filter is shown in Figure 4. The GA roll/pitch gain estimators are used to estimate the roll and pitch angles gain ($g_{1,r}/g_{1,p}$) of adaptive α_1 - β_1 - γ_1 filters. The GA tracking gain estimator is used to estimate the optimal gain \mathbf{g}_2 of adaptive α_2 - β_2 - γ_2 filter. The flow chart of GA tracking gain estimator is similar to Figure 4. The GA method uses selection, crossover, and mutation [16] techniques to find the solutions. At first, the initial population which contains randomly generated chromosomes is made. Chromosomes are chains of 0 and 1 bits whose length is defined as string length. Chromosomes number is defined as the population size. These chromosomes from the mating pool are shuffled to

create more randomness and then applied to the problem to find their outputs and fitness scores accordingly. Fitness value defines how well the chromosome solves the problem. Two chromosomes are selected from the mating pool depending on selection method. Depending on the crossover rate, all bits between two randomly chosen points selected from two different chromosomes are interchanged, which is known as two-point crossover. Chromosomes may undergo mutation where random bits of chromosomes are flipped depending on the mutation rate. Termination criteria are defined by the number of generations.

Selection is done usually by using two methods as follows: roulette wheel selection and tournament selection.

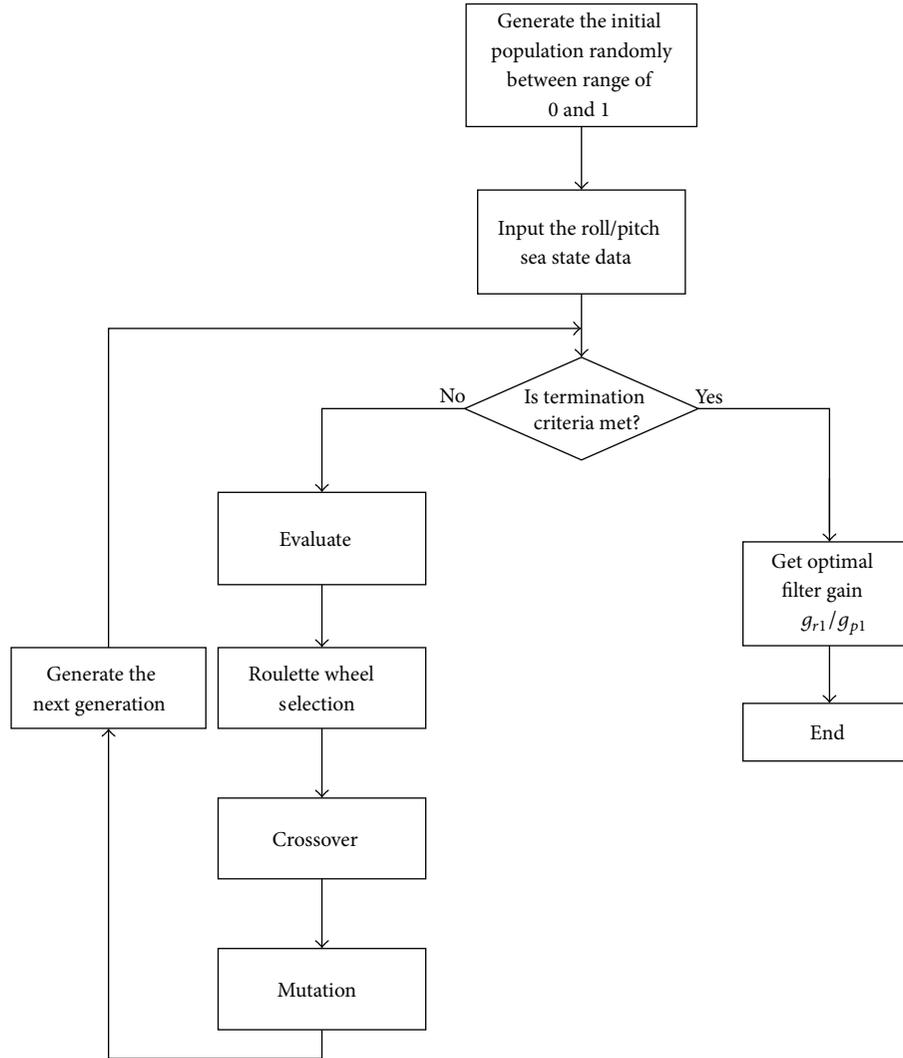


FIGURE 4: Flow chart of GA roll/pitch gain estimator.

In roulette wheel selection, the chromosomes selected from population are put into a mating pool. The chromosome selection probability is proportion to the fitness value. In tournament selection, chromosomes have to go through several tournaments. The chromosome, which has the fittest value, is selected and put into the mating pool. Here the roulette wheel selection method is chosen to determine the solution.

Two-point crossover calls for two random points selected from two different parent chromosome strings; all bits between two points are swapped for two parent chromosomes. Crossover rate is commonly chosen in a range of 0.60 to 0.80 [16]. Mutation rate describes the probability that a bit in a chromosome will be flipped (0 flips to 1 and 1 flips to 0). Mutation brings diversity to the population as mutation of a chromosome is a random process which will bring randomness to present chromosome group. Generation defines iteration, the GA method runs for a defined number of generations, and the final best solution is considered as the result.

3.4. *PSO Gain Estimator* [9, 12, 17]. PSO method was first proposed in [18]. PSO is based on the number of particles flying around the solution space to find the best solution that minimizes the cost function. Particles move around the solution space as soon as a particle detects a better solution; the information is passed to other particles and then particles change their position with respect to their best position observed among all the particles. Figure 5 describes the PSO method in detail. The PSO changes the velocity and position of the particle according to (15) and (17), respectively, to achieve the fitness [16]:

$$v_{id(n+1)} = K * [v_{id(n)} + c_1 \cdot \text{rand}() \cdot (p_{id(n)} - x_{id(n)}) + c_2 \cdot \text{Rand}() \cdot (p_{gd(n)} - x_{id(n)})], \quad (15)$$

$$K = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}, \quad \text{where, } \varphi = c_1 + c_2, \varphi > 4, \quad (16)$$

$$x_{id(n+1)} = x_{id(n)} + v_{id(n)}, \quad (17)$$

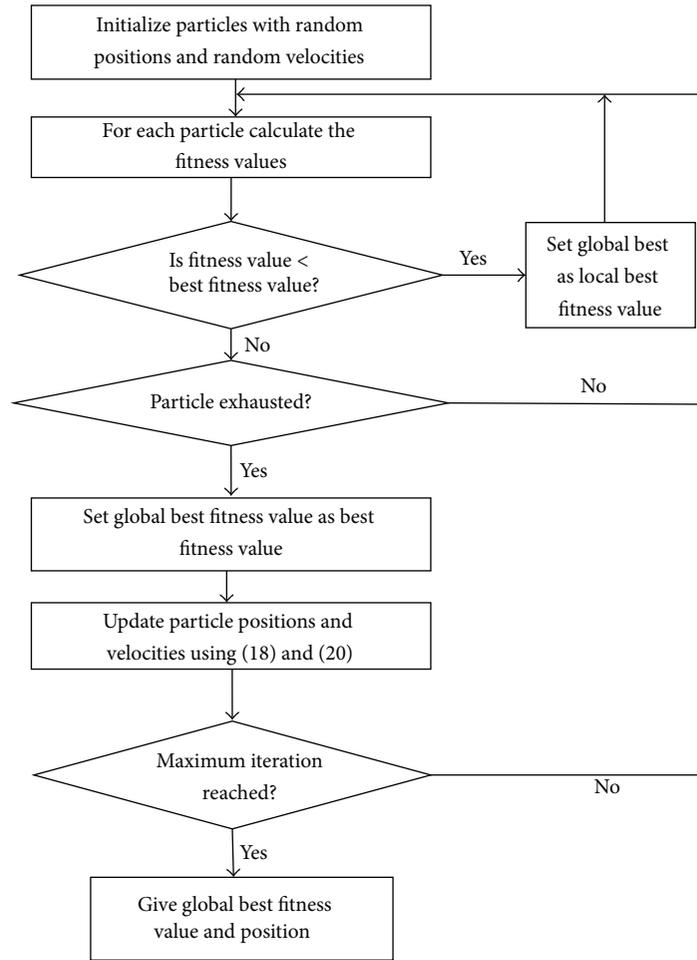


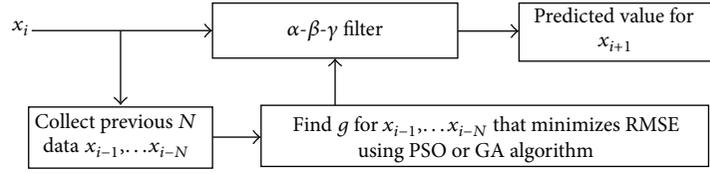
FIGURE 5: Flow chart of PSO method.

where $x_{id(n)}$ and $v_{id(n)}$ are position and velocity of (id)th particle at (n)th iteration, respectively. $p_{id(n)}$ and $p_{gd(n)}$ are the best position and global best position of (id)th particle at (n)th iteration, respectively. $\text{Rand}()$ and $\text{rand}()$ are random number between 0 and 1, respectively. Equation (15) updates the velocity of the particles and (17) updates the position of particles. K means inertia, c_1 and c_2 are correction factors, and swarm size means number of particles for an iteration, as described in [16].

Particles in the PSO method sometimes go out of constraints while changing their position. Reinitialization of the particle's position randomly to fall within the constraints is done as soon as a particle moves out of constraints. This ensures full use of particles and also increases the chance of discovering a better solution. To reduce the chance of getting trapped in a local minimum, the advantages of using PSO method are that it is derivative-free, easy to implement, and easy to comprehend and the solution is independent of the initial point [17]. One of the drawbacks of the PSO method is that it does not guarantee success; that is, the solution found may not be the best solution.

3.5. GA/PSO Based Adaptive α - β - γ Filter. The flow chart of the adaptive α - β - γ filter algorithm is shown in Figure 6, where N is the number of sampling data to determine the filter gain. In this algorithm, the parameters α , β , and γ , which are related to the filter gain g , are optimized by minimizing the RMSE using GA or PSO method. The proposed adaptive α - β - γ filter processes the current sampled data x_i which predicts the next sample data x_{i+1} as iteration continues. The adaptive GA or PSO process only occurs at certain time interval. The previous N data, that is, $x_p(i-N) \cdots x_p(i-1)$, is sent to the adaptive GA or PSO algorithm where the optimum value of filter gain (g) is determined for the α - β - γ filter. Then x_{i+1} is predicted and the process continues. The value of N determines running time and accuracy of the algorithm, so N must have small enough value to support real time implementation and large enough value to provide acceptable accuracy.

Since the roll and pitch angles of ship motion change over time randomly, in order to speed up the processing time and to reach the objectives of minimum estimation error, the filter gain values are real time updated by using the pipelined architecture. The recorded roll and pitch signals are

FIGURE 6: Block diagram of adaptive α - β - γ filter.

segmented into block of 1000 sampled data (100 sec) for linear trajectory target and 420 sampled data (42 sec) for circular trajectory target, respectively. The gain value of α_2 - β_2 - γ_2 filter in 101–200 sec is estimated by GA and PSO methods using the collected data during 1–100 sec, the gain value of α_2 - β_2 - γ_2 filter in 201–300 sec is estimated by the GA and PSO methods using the collected data in 101–200 sec, and so on. Similarly, the measured flight target signals are segmented into block of 100 sampled data (100 sec) for linear trajectory target and 42 sampled data (42 sec) for circular trajectory target, respectively. The gain value of α_2 - β_2 - γ_2 filter in 101–200 sec is estimated by the GA and PSO methods using the collected data during 1–100 sec, the gain value of α_2 - β_2 - γ_2 filter in the interval of 201–300 sec is estimated by the GA and PSO methods using the collected data in 101–200 sec, and so on.

For the PSO process, it was found that gain parameter converged within 100 iterations, so the number of iterations for an adaptive α - β - γ filter was kept at constant 100 iterations per processing cycle, swarm size = 30, inertia = 0.7298, and correction factors $c_1 = 2.1$, $c_2 = 2$. For the GA process, we have considered population size = 8, string length = 12, crossover rate = 0.8, and mutation rate = 0.05.

If $\theta_{i,p}$, $i = 1, 2, \dots, N$ and $\hat{\theta}_{i,p}$, $i = 1, 2, \dots, N$ are real measurement pitch's values and estimated pitch's values of adaptive α_1 - β_1 - γ_1 filter, respectively, then $\theta_{i,r}$, $i = 1, 2, \dots, N$ and $\hat{\theta}_{i,r}$, $i = 1, 2, \dots, N$ are real measurement roll's values and estimated roll's values of adaptive α_1 - β_1 - γ_1 filter, respectively, where i is the current iteration and N is the total number of sampling data. The RMSEs of pitch and roll estimations are defined as follows:

$$\text{RMSE}_p = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{\theta}_{i,p} - \theta_{i,p})^2}, \quad (18)$$

$$\text{RMSE}_r = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{\theta}_{i,r} - \theta_{i,r})^2}, \quad (19)$$

where the main purpose of GA and PSO methods is to find the optimum values of $g_{1,p}$ and $g_{1,r}$ which minimize the RMSE_p and RMSE_r , respectively.

If \mathbf{X}_i and $\hat{\mathbf{X}}_i$, $i = 1, 2, \dots, N$ are real measurement target position vector values and estimated target position vector

values of adaptive α_2 - β_2 - γ_2 filter, the RMSE of target tracking is defined as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N ((x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (z_i - \hat{z}_i)^2)}, \quad (20)$$

where x_i , y_i , and z_i are the components of target position vector \mathbf{X}_i in x , y , and z axes. The main purpose of GA and PSO algorithms is to find the optimum gain value of \mathbf{g}_2 which minimizes the RMSE.

4. Experimental Results

Six scenarios are used to simulate the tracking performance of ship-borne phased array radar using the proposed adaptive α - β - γ filter for beam pointing error compensation and target tracking in three-dimensional space.

Case 1 (roll and pitch estimations using GA based adaptive α - β - γ filter and measured data). The roll and pitch data recorded by a gyroscope of the ship were used in the experiments. The total number of data is 1000 and the sampling time is 0.1 sec. The angle variation of roll and pitch signals measured by ship gyroscope are shown in Figure 7, which will result in the beam pointing errors of phased array antenna. The GA based adaptive α - β - γ filter is used to estimate the roll and pitch angles. Figures 8(a) and 8(b) show that the convergent time of roll and pitch angles are 3 sec and 5 sec, respectively, under simulated sea states 2 and 3 and measured data. The ship's roll and pitch signals are simulated according to (3) and (4) with roll and pitch angle parameters of sea states 2 and 3 listed in Table 1 and standard deviation of 0.01. It concludes that the proposed GA based adaptive α - β - γ filter is suitable to compensate the ship motion. As shown in Table 1, the period of sea state 2 is longer than sea state 3. Therefore, the convergent RMSE (about 0.19° for roll, about 0.1° for pitch) of sea state 2 is less than sea state 3 (about 0.29° for roll, about 0.22° for pitch) because the roll and pitch signals with shorter period in sea state 3 have rapid oscillations, which are more difficult to be predicted precisely.

Case 2 (tracking linear moving target in three-dimensional space using GA based adaptive α - β - γ filter (without beam pointing error)). Assuming the ship is not affected by the sea waves (antenna beam pointing error is zero), the tracking performance of GA based adaptive α - β - γ filter for a straight flight target trajectory is simulated. The initial position of radar is (0, 0, 0). The ship moves with a speed of 10 m/sec in

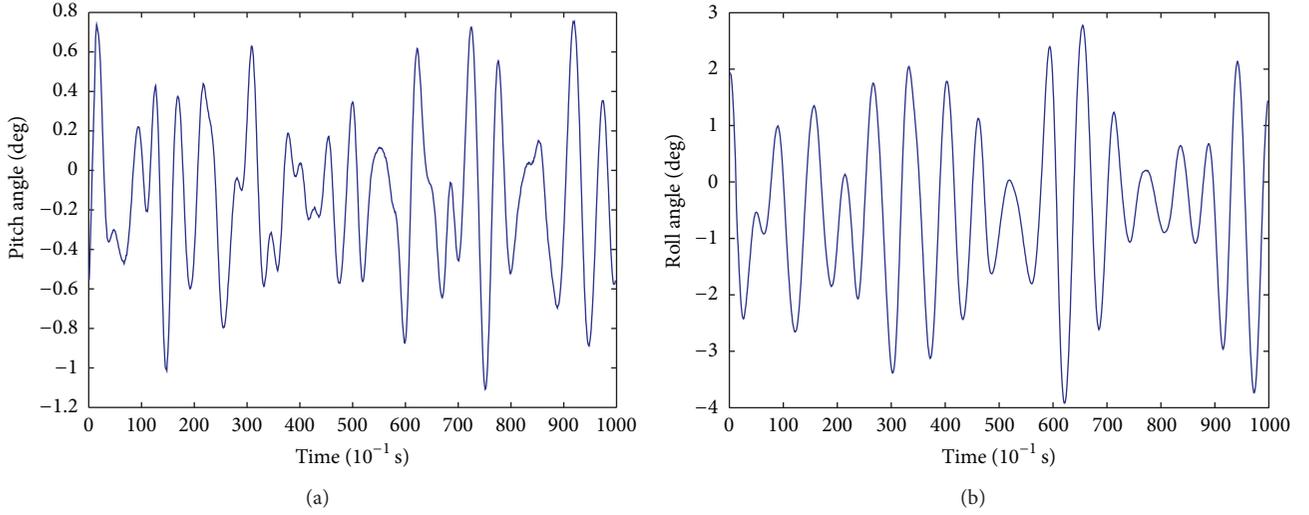


FIGURE 7: Demonstrating angle variation of (a) pitch and (b) roll signals measured by gyroscope.

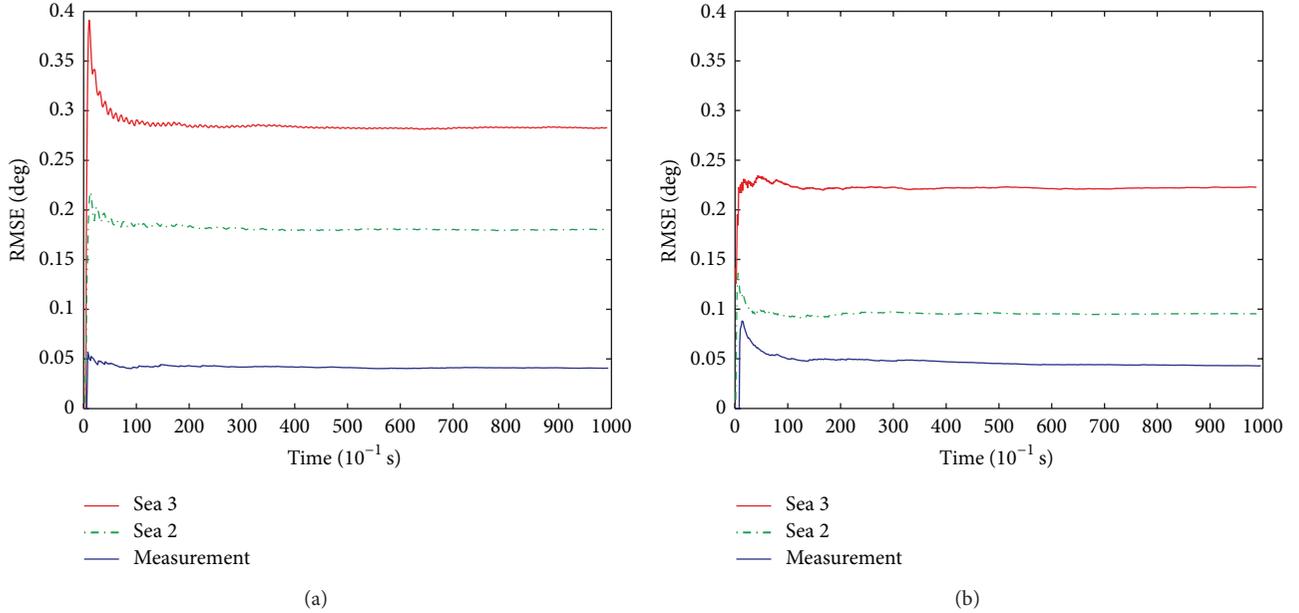


FIGURE 8: RMSE of (a) roll and (b) pitch under simulated data of sea states 2 and 3 and measured data.

the Y axial direction. The linear path equation of the ship is given by

$$\mathbf{X}_s(x_t, y_t, z_t) = \mathbf{X}_{0s} + \mathbf{V}_s t, \quad (21)$$

where $t = 1, 2, 3, \dots, 1000$ sec, \mathbf{V}_s is ship velocity vector and \mathbf{X}_{0s} is initial ship position vector in three-dimensional space. The radar position is updated every second. The initial position of flying target is $(-74840, -129620, 9100)$ m, which is about 150 km from the radar. The flight speed of target is 300 m/sec (X axial velocity of 150 m/sec and Y axial velocity of 260 m/sec). The target location is updated every second. The linear target trajectory equation is

$$\mathbf{X}_m(x_t, y_t, z_t) = \mathbf{X}_{0m} + \mathbf{V}_m t, \quad (22)$$

where \mathbf{V}_m is the target velocity vector and \mathbf{X}_{0m} is the initial target position vector in three-dimensional space. The tracking accuracy of GA based adaptive α - β - γ filter for a straight flight target is shown in Figure 9, where the trajectory estimation error is calculated by

$$E_t = \sqrt{(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2 + (z_t - \hat{z}_t)^2}, \quad (23)$$

where (x_t, y_t, z_t) and $(\hat{x}_t, \hat{y}_t, \hat{z}_t)$ denote the real target location and estimated target location, respectively. It shows that the GA based adaptive α - β - γ filter converges to less than about 2 m after 5 sec.

TABLE 2: Estimated gain parameters for GA based adaptive α - β - γ filter.

Time (sec)	1~100	101~200	201~300	301~400	401~500	501~600	601~700	701~800	801~900	901~1000
$g_{r,1}$	0.574	0.6399	0.652	0.6904	0.6537	0.674	0.6286	0.6313	0.6044	0.5392
$g_{p,1}$	0.629	0.6664	0.622	0.7756	0.664	0.7399	0.663	0.6652	0.6816	0.6498
g_2	0.285	0.5827	0.3282	0.3851	0.0054	0.3480	0.2916	0.3736	0.547	0.4864

TABLE 3: Estimated gain parameters for PSO based adaptive α - β - γ filter.

Time (sec)	1~100	101~200	201~300	301~400	401~500	501~600	601~700	701~800	801~900	901~1000
$g_{r,1}$	0.557	0.5986	0.357	0.5345	0.6142	0.5774	0.5544	0.529	0.4592	0.5626
$g_{p,1}$	0.612	0.5898	0.4129	0.5675	0.5286	0.3953	0.5565	0.6199	0.5214	0.6285
g_2	0.326	0.07	0.1136	0.146	0.098	0.2365	0.21	0.2547	0.2474	0.1245

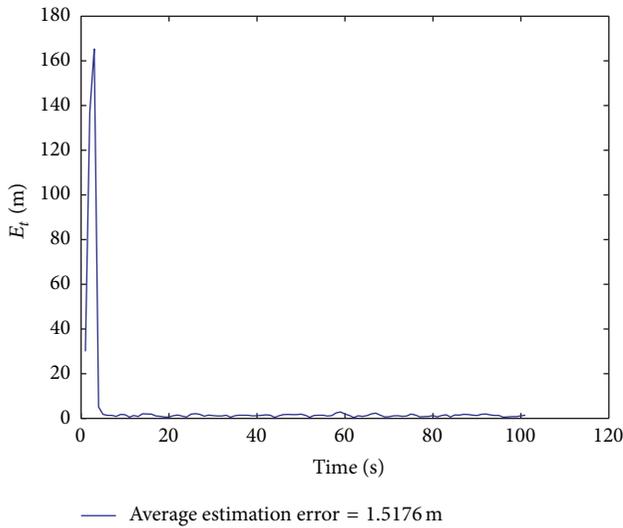


FIGURE 9: Estimation error for linear target trajectory without beam pointing error.

Case 3 (tracking circular moving target in three-dimensional space using GA based adaptive α - β - γ filter (without beam pointing error)). Figures 10(a) and 10(b) show the simulation scenario of beam pointing error compensation for circular maneuvering air target and linear moving ship. The ship has the same linear moving speed and path equation as Case 2. The flying target is parallel to the XY plane, the initial position of flying target is (8885, 4590, 9100) m, the velocity is 300 m/sec, and the angle (θ_0) between the initial position and the X-axis is 30° . The trajectory of the flight vehicle is a circle, which has a radius of 10 km. The center of circular trajectory is Y-axis. The rotational cycle time of the flight target is 209 seconds and the total observation time is 419 sec.

The circular trajectory equation is

$$\mathbf{X}_m(x_t, y_t, z_t) = (r \cos(\theta_0 - \omega t), r \sin(\theta_0 - \omega t), 9100), \quad (24)$$

where $t = 1, 2, 3, \dots, 418, 419$ sec, r is the circular flight radius in meter, θ_0 is the initial angle between the flight vehicle, and the X-axis, ω is the angular speed of flight vehicle. The accuracy of GA based adaptive α - β - γ filter for tracking a circular flight target is shown in Figure 11, where the GA based adaptive α - β - γ filter converges to less than 3 m after 8 sec. Therefore, using the GA based adaptive α - β - γ filter to track the circular trajectory target has the larger average estimation error and longer convergent time than linear trajectory target.

Case 4 (estimating roll and pitch angles and tracking linear trajectory target using GA/PSO based adaptive α - β - γ filter and measured data (with beam pointing error)). The measured roll and pitch signals shown in Figure 7 are used to evaluate the performance of GA/PSO based adaptive α - β - γ filter for estimating the roll and pitch angles and tracking the linear trajectory target. The beam of 6×6 planar array antenna is steered to track the linear trajectory target. The sampling frequency is set as 10 Hz. Therefore, the ship's roll and pitch signals are sampled 10000 points within 1000 seconds. As the scenario described in Case 2, the ship is along the Y axis of XY plane in the earth coordinates, the ship speed is 10 m/sec, and the flying target speed is 300 m/sec. The flying target is parallel to the XY plane, 9.1 km above the ground, and the angle between the flight direction and the Y-axis is 120° . The largest reconnaissance distance of ship-borne radar is 150 km. When the air target is flying within the radar detection range, the beam pointing error estimation and linear trajectory target tracking of ship-borne phased array radar are simulated.

Figure 12 is a simulation flow chart used to verify the effect of beam pointing error compensation on the tracking accuracy of adaptive α - β - γ filter. Tables 2 and 3 demonstrate the optimal gain parameters of adaptive α - β - γ filter for roll $g_{r,1}$, pitch $g_{p,1}$, and target tracking g_2 obtained by the GA and PSO methods, respectively, that minimizes the RMSE. Figures 13–17 show the estimation errors for five different gain values, which are summarized in Table 4. It demonstrates that the greater gain value ($g = 0.1, 0.75$ and 0.9) will generate the greater error and need the longer convergence time. The estimation errors

TABLE 4: Estimation errors for different gains.

	Calculated by GA	Calculated by PSO	Fixed gain		
$g_{r,1}$	0.5392~0.6904	0.357~0.6142	0.1	0.75	0.9
$g_{p,1}$	0.622~0.7756	0.3953~0.6285	0.1	0.75	0.9
g_2	0.054~0.5827	0.07~0.3259	0.1	0.75	0.9
Average E_t (m)	14.781	16.3224	16.9663	53.4804	399.1188

TABLE 5: Estimated gain parameters for GA based adaptive α - β - γ filter.

Time (sec)	1~100	101~200	201~300	301~400	401~500	501~600	601~700	701~800	801~900	901~1000
$g_{r,1}$	0.543	0.5653	0.5424	0.5455	0.5665	0.56	0.58	0.532	0.5414	0.5385
$g_{p,1}$	0.464	0.484	0.4459	0.422	0.4667	0.4654	0.4509	0.4459	0.4308	0.4651
g_2	0.161	0.0929	0.1937	0.0865	0.0241	0.0609	0.1174	0.1897	0.1713	0.1727

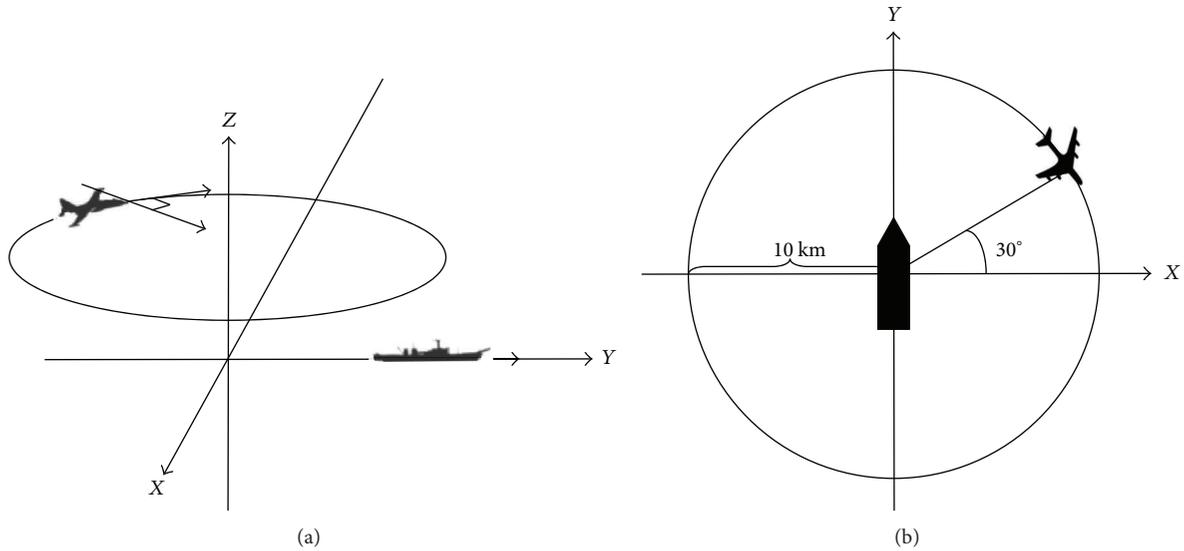


FIGURE 10: Simulation scenarios of Case 3 for (a) 3D and (b) top view diagrams.

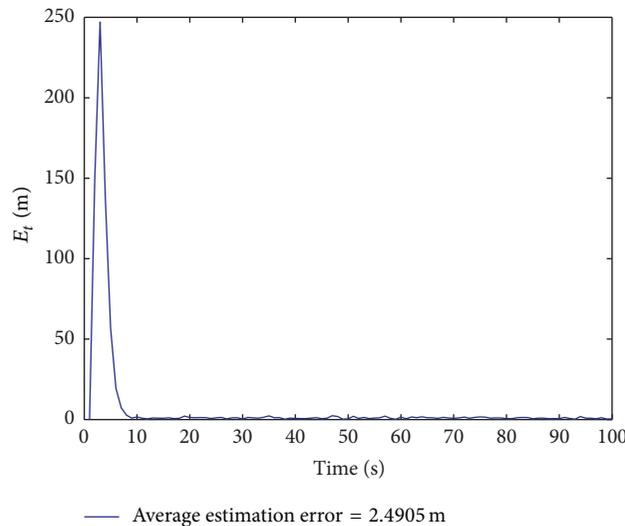


FIGURE 11: Estimation error for circular target trajectory without beam pointing error.

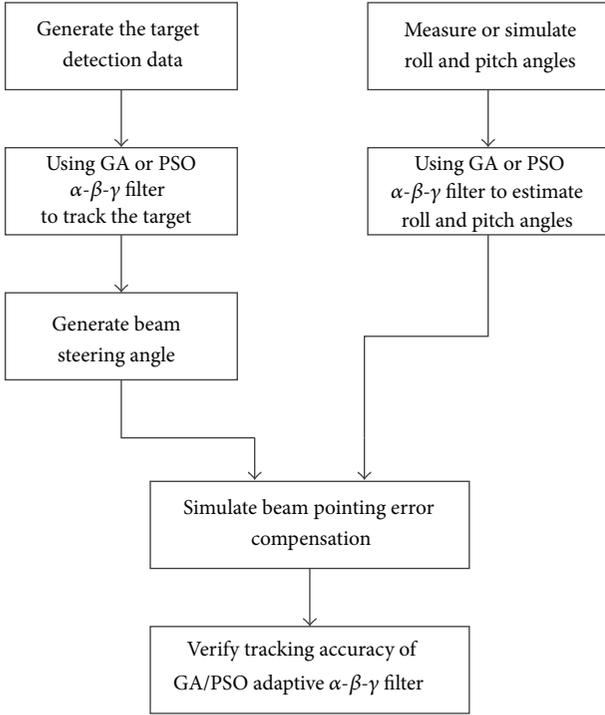


FIGURE 12: Flow chart of tracking performance simulation for Case 4 experiment.

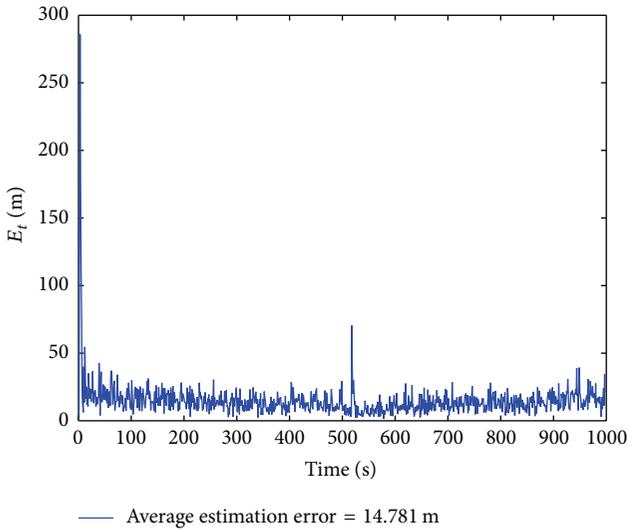


FIGURE 13: Estimation error of GA based adaptive α - β - γ filter.

presented in Figures 16 and 17 are too large to be applicable when the gain values are equal to 0.75 and 0.9. The GA and PSO have smaller errors compared with the fixed gain values, and the GA obtains the best estimation accuracy. The estimation errors of GA and PSO methods were found to be close. From Figures 13, 14, and 15, we can observe that there is a peak value that occurred at the time duration about 510 to 515 seconds, because the horizontal beam direction of ship-borne phased array

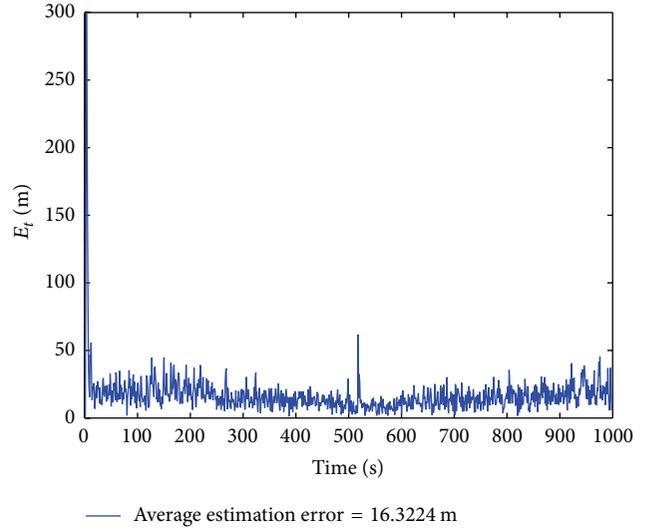


FIGURE 14: Estimation error of PSO based adaptive α - β - γ filter.

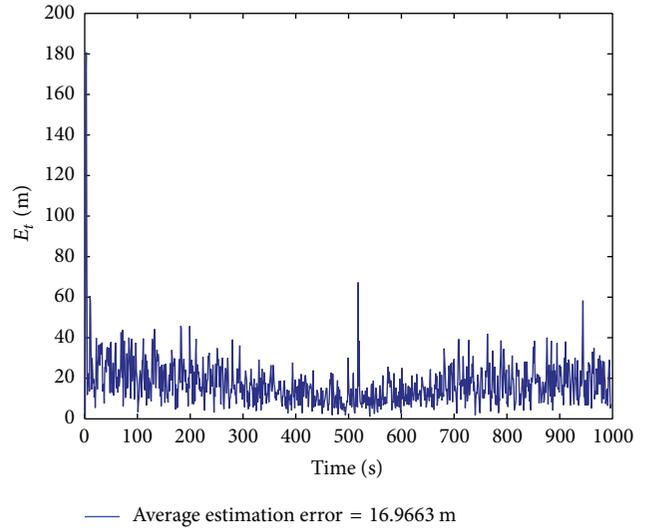


FIGURE 15: Estimation error of α - β - γ filter with $g_{r,1} = g_{p,1} = g_2 = 0.1$.

radar is steered according to the linear trajectory target, which is flying through sky just above the ship at the time instant of 510 second. As shown in Figure 18, the horizontal beam steering angle of ship-borne phased array radar at about the time of 510 second is changing from descending into ascending. When the GA based adaptive α - β - γ filter tracks the linear trajectory target, the estimation error values are less than 30 meters or less if the peak estimation errors during these 5 seconds are ignored.

Case 5 (estimating roll and pitch angles and tracking linear trajectory target using GA/PSO based adaptive α - β - γ filter and simulated data (with beam pointing error)). The ship's roll and pitch signals are simulated according to (3) and (4) with parameters of sea state 2 listed in Table 1 and standard

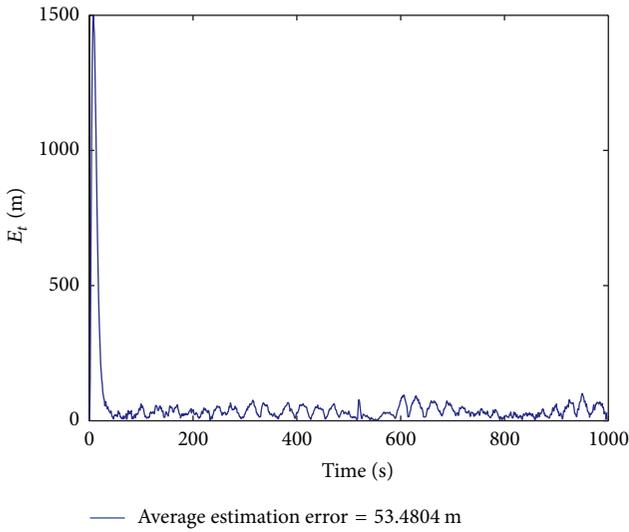


FIGURE 16: Estimation error of α - β - γ filter with $g_{r,1} = g_{p,1} = g_2 = 0.75$.

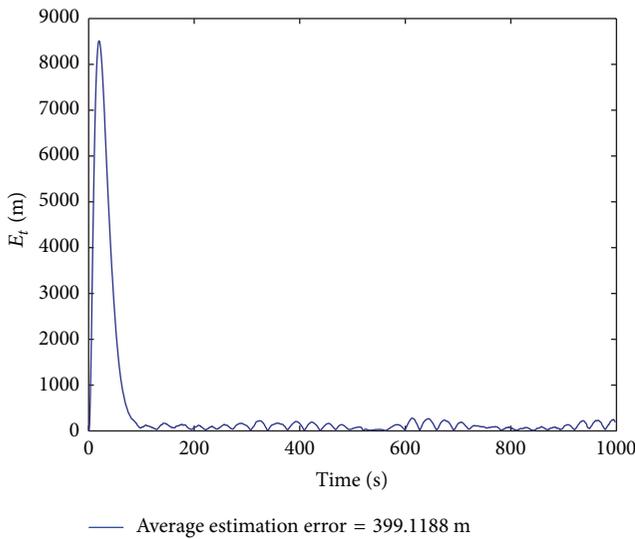


FIGURE 17: Estimation error of α - β - γ filter with $g_{r,1} = g_{p,1} = g_2 = 0.9$.

deviation of 0.01. The simulated ship's roll and pitch signals are applied for five different methods to estimate the gain of GA/PSO based adaptive α - β - γ filter. The total observation time is 1000 sec and sampling time is 0.1 sec. The simulation replicates 10000 times. The input samples are updated by one new sample for the next iteration. The other simulation scenario and parameters are the same as Case 4. Tables 5 and 6 demonstrate the optimal gain parameters of adaptive α - β - γ filter for roll gain $g_{r,1}$, pitch gain $g_{p,1}$, and target tracking gain vector \mathbf{g}_2 obtained by the GA and PSO methods, respectively, that minimizes RMSE. Figures 19, 20, 21, 22, and 23 show the estimation errors for five different gain values, which are summarized in Table 7. The estimation error of GA based adaptive α - β - γ filter for tracking a linear trajectory target is shown in Figure 19, where the convergence time of GA

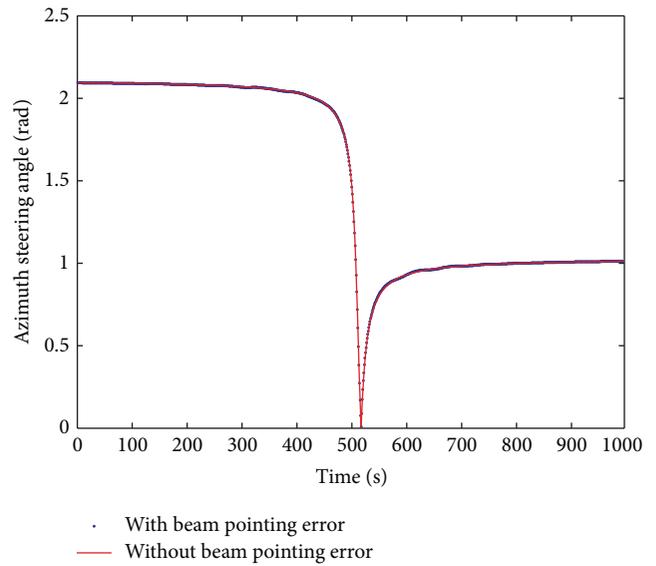


FIGURE 18: Azimuth beam steering angle of ship-borne phased array radar.

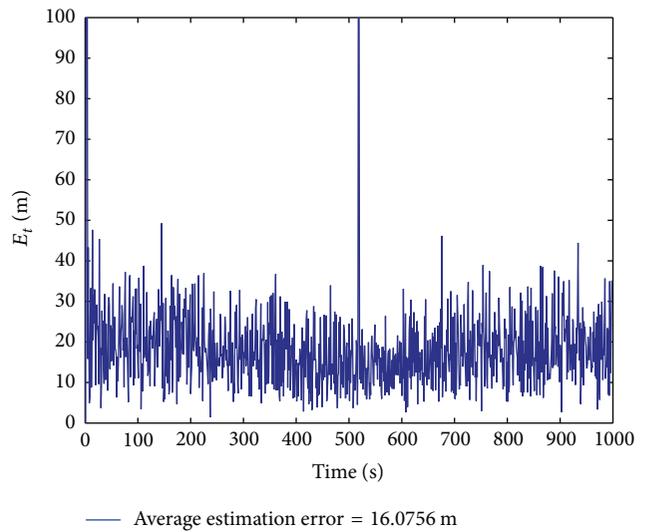
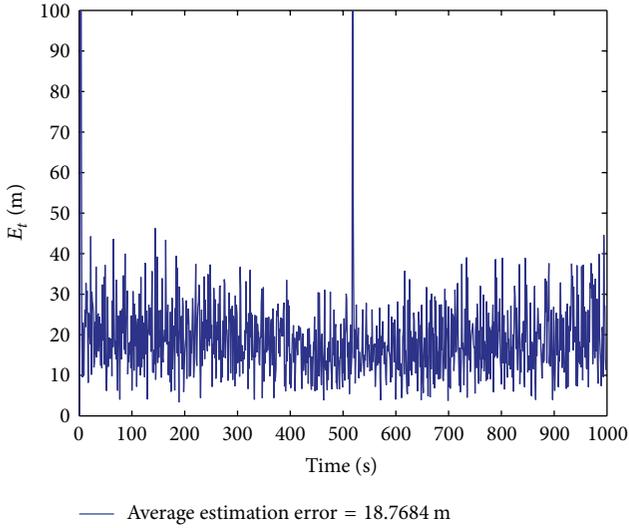
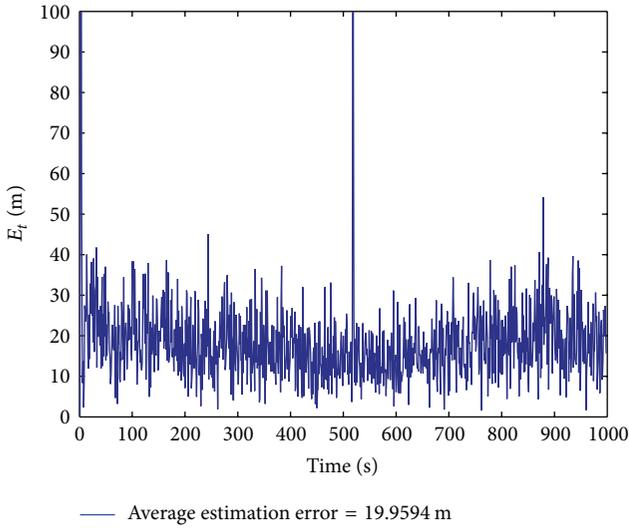


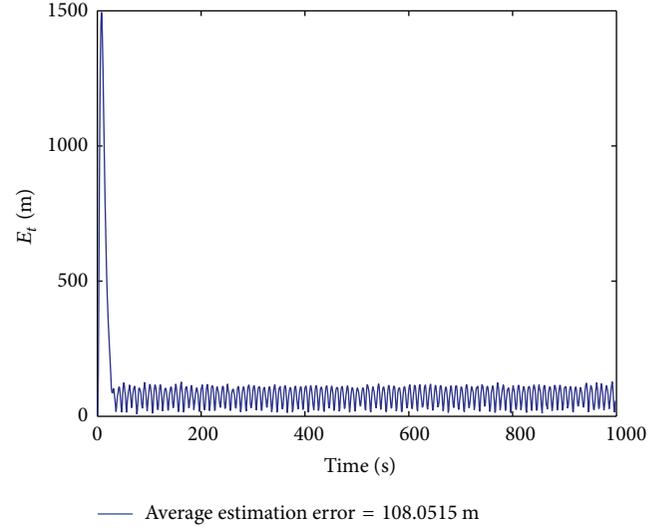
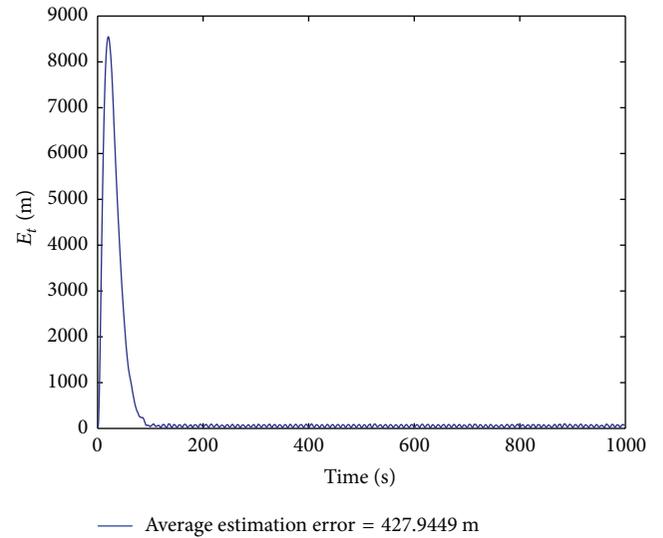
FIGURE 19: Estimation error of GA based adaptive α - β - γ filter.

based adaptive α - β - γ filter is about 3 sec and the average estimation error is about 16.0756 m. It concludes that the experimental results in Case 5 have the same trend as in Case 4; therefore, the simulated data can be used to observe the effect of ship motion on the tracking performance of ship-borne phased array radar under different sea state conditions. The convergence time and average estimation error of GA based adaptive α - β - γ filter are better than the method used in [6], where the tracking error of AEKF converges to less than about 20 m at 550 iterations (sec/iteration) and the estimation error will remain within the range of about 20 m when the beam pointing error is compensated by FBFN controller.

Case 6 (estimating roll and pitch angles and tracking circular moving target using GA based adaptive α - β - γ filter and

FIGURE 20: Estimation error of PSO based adaptive α - β - γ filter.FIGURE 21: Estimation error of α - β - γ filter with $g_{r,1} = g_{p,1} = g_2 = 0.1$.

measured data (with beam pointing error)). As the scenario described in Case 3, the measured roll and pitch signals shown in Figure 7 are used to evaluate the performance of GA based adaptive α - β - γ filter for estimating the roll and pitch angles and tracking the circular trajectory target. The estimation errors of α - β - γ filter with fixed gains of $g_{r,1} = g_{p,1} = g_2 = 0.1$ and $g_{r,1} = g_{p,1} = g_2 = 0.75$ are shown in Figures 24 and 25, respectively. The average estimation errors for fixed filter gains of 0.1 and 0.75 are about 4.1638 m and 57.2386 m, respectively. The optimal roll gain $g_{r,1}$, pitch gain $g_{p,1}$, and target tracking gain g_2 of adaptive α - β - γ filter estimated by the GA method during the observation time of 419 sec are listed in Table 8. The estimation error of GA based adaptive α - β - γ filter for tracking a circular flight target is shown in Figure 26, where the convergence time of GA based adaptive α - β - γ filter is about 5 sec and the average

FIGURE 22: Estimation error of α - β - γ filter with $g_{r,1} = g_{p,1} = g_2 = 0.75$.FIGURE 23: Estimation error of α - β - γ filter with $g_{r,1} = g_{p,1} = g_2 = 0.9$.

estimation error is about 3.6667 m. It concludes that the GA based adaptive α - β - γ filter can greatly improve the tracking accuracy and convergence time of the conventional α - β - γ filter for tracking the circular trajectory target.

5. Conclusions

This paper proposed an intelligent beam pointing error compensation mechanism for ship-borne phased array radar. The GA based adaptive α - β - γ filter estimates the roll and pitch angles of the ship moving in the sea and thus compensates for the antenna beam pointing error in order to enhance the tracking accuracy of phased array radar system.

TABLE 6: Estimated gain parameters for PSO based adaptive α - β - γ filter.

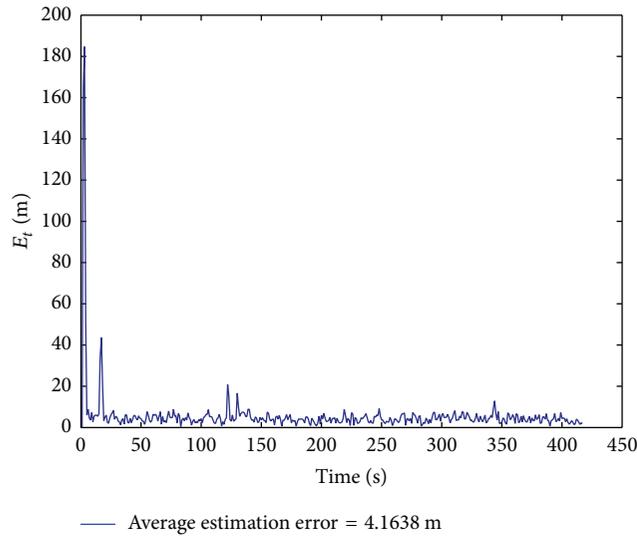
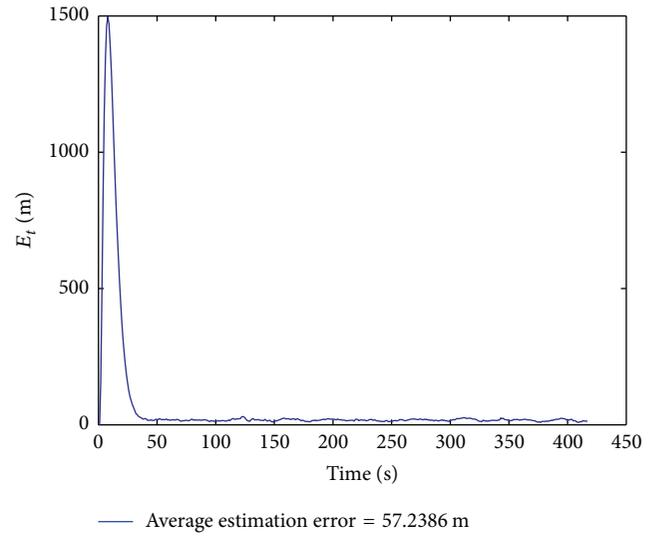
Time (sec)	1~100	101~200	201~300	301~400	401~500	501~600	601~700	701~800	801~900	901~1000
$g_{r,1}$	0.366	0.3645	0.532	0.4519	0.5151	0.5002	0.4797	0.5254	0.4146	0.5351
$g_{p,1}$	0.366	0.3647	0.3634	0.3644	0.3643	0.363	0.3644	0.3684	0.3643	0.3642
g_2	0.125	0.1271	0.2286	0.2166	0.1169	0.1799	0.1735	0.1564	0.0767	0.1346

TABLE 7: Estimation errors for different gains.

	Calculated by GA	Calculated by PSO	Fixed gain
$g_{r,1}$	0.459~0.583	0.3645~0.5352	0.1
$g_{p,1}$	0.498~0.667	0.363~0.3684	0.1
g_2	0.0586~0.1697	0.0367~0.2291	0.1
Average E_t (m)	16.0756	18.7684	19.9594

TABLE 8: Estimated gain parameters for GA based adaptive α - β - γ filter.

Time (sec)	1~42	43~84	85~126	127~168	169~210	211~252	253~294	295~336	337~378	379~419
$g_{r,1}$	0.619	0.4996	0.5316	0.644	0.5052	0.5568	0.5316	0.4459	0.5092	0.5924
$g_{p,1}$	0.582	0.6727	0.7201	0.4913	0.4168	0.7169	0.5983	0.2036	0.5858	0.621
g_2	0.214	0.2215	0.1612	0.2474	0.1822	0.157	0.2073	0.1211	0.2278	0.1074

FIGURE 24: Estimation error of α - β - γ filter with $g_{r,1} = g_{p,1} = g_2 = 0.1$.FIGURE 25: Estimation error of α - β - γ filter with $g_{r,1} = g_{p,1} = g_2 = 0.75$.

Six experimental cases are conducted to verify the performance of ship-borne phased array radar using the proposed GA based adaptive α - β - γ filter. In Case 1, the GA based adaptive α - β - γ filter is used to estimate the roll and pitch angles with the simulated and measured roll and pitch signals, respectively. The simulation results show that the measurement data has the minimum estimation error, the estimation error in the sea state 2 is the second, and the estimation error in the sea state 3 is the worst. Cases 2 and 3 show that when the GA based adaptive α - β - γ filter is applied to estimate the beam pointing error and to track the target in a ship-borne phased array radar, the circular trajectory

target will be tracked with the larger average estimation error and longer convergence time than linear trajectory target. The experimental results of Cases 4 and 5 demonstrate that when a linear trajectory target is tracked by ship-borne phased array radar, the average estimation error and convergence time of ship-borne phased array radar using the GA based adaptive α - β - γ filter are better than PSO based adaptive α - β - γ filter and fixed filter gain α - β - γ filter. The convergence time and tracking accuracy of ship-borne phased array radar using the proposed GA based adaptive α - β - γ filter are superior to the AEKF significantly. In conclusions, the proposed GA based adaptive α - β - γ filter is a real time applicable algorithm

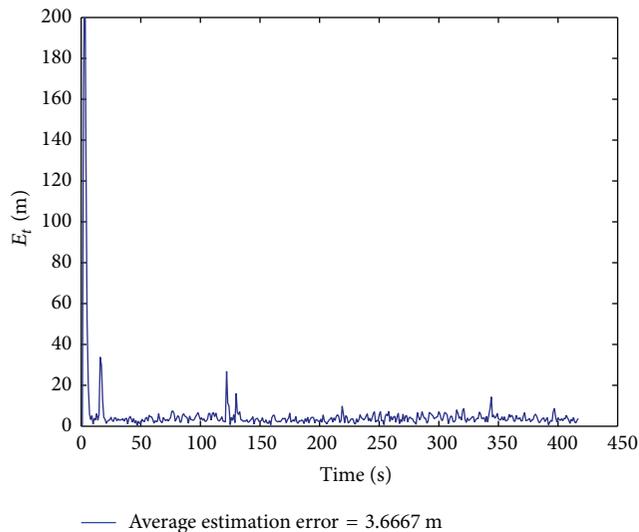


FIGURE 26: Estimation error of GA based adaptive α - β - γ filter.

whose accuracy is good with relatively less complexity. In addition, the roll and pitch signals measured in real operation environments can be replaced with the simulated roll and pitch signals to test all the relevant properties of practical ship motion compensation and air target tracking for ship-borne phased array radar.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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