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Research Article

IMPROVED NONLINEAR STOCHASTIC ESTIMATOR FOR ELECTRONIC SUPPORT MEASUREMENTS IN ELECTRONIC WARFARE

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ABSTRACT

Objective: Inclusion of range, course, and speed parameterization is proposed in target state vector of modified gain bearings-only extended Kalman filter to obtain fast convergence and to track a stationary/nonstationary target.

Methods: In electronic warfare (EW), electronic support measurement systems, the transmissions made by radar on a target ship are assumed to be intercepted by an EW system of ownship.

Results: Time to estimate the target motion parameters with reasonable accuracy is highly dependent on the values used for initialization of target state vector components.

Conclusion: The performance of the algorithm is evaluated in simulation, and results are presented for two selected scenarios.

Keywords: Kalman filter, Electronic warfare systems, Simulation, Estimation theory.

INTRODUCTION

Surveillance is the most important facet of maritime warfare and is undertaken by active as well as passive sensors. Dynamic strategies for reconnaissance require acoustic transmissions to be made by the observation stage and consequently powerless to capture attempt by others. Subsequently, in certain strategic circumstances, it gets to be important to utilize aloof mode. In this paper, it is expected that ownship gets the bearing estimations of the objective at whatever point it is in transmission mode. An electronic warfare (EW) beneficiary introduced on ownship catches the estimations emanated by radar housed on an objective boat, which is thought to be stationary or moving at consistent speed. EW collector creates bearing estimations of the objective boat. The objective is thought to be in the dynamic method of transmission. This technique gives quick estimation of orientation of emitter and not its reach.

In the sea environment, two-dimensional orientation just target movement examination is for the most part taken after. The bearing estimations produced by uninvolved sensors are adulterated with clamor. The ownship forms these estimations and discovers target movement parameters - *viz*., range, course, bearing, and speed of the objective. Here, the estimation is nonlinear, making the entire procedure nonlinear. For perceptibility of the procedure, ownship completes S-move on viewable pathway.

Established least square estimator and Kalman channel cannot be specifically connected. The customary Kalman channel is ideal when the model is direct. Tragically, a hefty portion of the state estimation issues like following of the objective utilizing course just data are nonlinear, in this way restricting the down to earth handiness of the Kalman filter and extended Kalman filter (EKF). The difference in EKF is disposed of by altering the addition function [1], and this calculation is named as modified gain bearings-just EKF (MGBEKF). The key thought behind MGBEKF is that the nonlinearities “modifiable.” A disentangled adaptation of the adjusted addition capacity was made accessible by Galkowski and Islam [2]. This calculation was further changed for submerged target following applications [3,4], where course just estimations are accessible.

As of late, the attainability of a novel change, known as unscented change, which is intended to proliferate data as mean vector and covariance framework through a nonlinear procedure, is investigated for submerged applications. The unscented change is combined with specific parts of the traditional Kalman channel. It is simpler to actualize and it utilizes the same request of estimations [5,6]. Unscented Kalman filter can be dealt with as other options to MGBEKF [7].

Particle filters [5,6,8,9] are the new era of cutting edge channels, which are valuable for nonlinear and non-Gaussian applications. Molecule channels or successive Monte Carlo strategies utilize an arrangement of weighted state tests, called particles, to surmised the back likelihood circulation in a Bayesian setup. Anytime of time, the arrangement of particles can be utilized to rough the probability density function of the state. More computational exertion is required for superior of the molecule channel. The cost that must be paid for the elite of the molecule channel is an expanded level of computational exertion.

The writers are roused by the work exhibited by “Branko Ristic, Sanjeev Arulampalam and Neil Gordon” in “Past the Kalman filter-particle channels for following applications” [5]. These researchers isolated the reach interim of enthusiasm into various sub-interims, and every sub-interim is managed a free Kalman channel. They proposed that this technique can be reached out to course and speed parameterization, if earlier information of target course and speed separately are obscure. Parameterization in introduction diminishes the reliance of joining of the arrangement on initialization [10]. In aloof target following, earlier learning of target boat range, course, and speed is ambiguous. The point is to gauge target movement parameters as precisely as would be prudent at the most punctual. Consideration of reach, course, and speed parameterization is proposed for MGBEKF to track an objective utilizing direction just estimations and this calculation is named as parameterized MGBEKF (PMGBEKF). In this paper, PMGBEKF is created to track an objective boat utilizing EW electronic support measures (ESMs) bearing estimations.

The ownship is thought to get ESM bearing estimations from EW collector. The estimations are not accessible at uniform time interim, as ESM orientation accessible at EW collector will be founded on the reception apparatus examine rate of the objective. ESM orientation input rate for hunt radar and track while check radar may shift from 2.5 to 20 seconds. In specific cases, when the objective is bolted on, the information sources will be accessible consistently. In spite of the fact that the bearing estimations are like latent sonar estimations, there are two noteworthy contrasts: (1) The clamor in the estimations in ESM estimations is in the request of 2° rms, while in the event of detached sonar, it is around 0.5° rms, (2) The estimation interim is not uniform, as target may utilize number of radars (each one in turn) working at various sweep rates.

PMGBEKF is developed and extensive simulation is carried out. The measurement is assumed to be available whenever the target ship is in active mode. The solution is updated, whenever, the measurement is received and the solution is extrapolated at the rate of one second. The estimated state vector is used to find out target motion parameters. Section 2 describes the mathematical formulation of the PMGBEKF. Simulation and results are presented in Section 3. The limitations of the algorithm are presented in Section 4, and finally, the paper is concluded in Section 5.

MATHEMATICAL MODELING

MGBEKF

The alternative derivation of the modified gain function [1] of Song and Speyer's EKF is slightly modified as follows. Let the target state vector be $X_s(k)$ where,

$$X_s(k)=\left[\dot{x}(k) \quad \dot{y}(k) \quad R_x(k) \quad R_y(k)\right]^T \tag{1}$$

Where, $\dot{x}(k)$ and $\dot{y}(k)$ are target velocity components and $R_x(k)$ and $R_y(k)$ are range components, respectively. The target state dynamic equation is given by:

$$X_s(k+1) = \varphi X_s(k)+b(k+1)+\Gamma\omega(k) \tag{2}$$

Where, φ and b are transition matrix and deterministic vector, respectively. The transition matrix is given by,

$$\varphi=\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ t & 0 & 1 & 0 \\ 0 & t & 0 & 1 \end{bmatrix}$$

Where, t is sample time,

$$b(k+1)=\left[0 \quad 0 \quad -\left(x_0(k+1)-x_0(k)\right) \quad -\left(y_0(k+1)-y_0(k)\right)\right]a$$

$$\text{and } \Gamma=\begin{bmatrix} t & 0 & t^2/2 & 0 \\ 0 & t & 0 & t^2/2 \end{bmatrix}^T \tag{3}$$

Where, x_0 and y_0 are ownship position components. The plant noise $\omega(k)$ is assumed to be zero mean white Gaussian with $E\left[w(k) \quad w'(j)\right]=Qd_{kj}$. All angles are considered with respect to Y-axis, 0 to 360° and clockwise positive to reduce mathematical complexity and for easy implementation. The bearing measurement, B_m is modeled as:

$$B_m(k+1)=\tan^{-1}\left(\frac{R_x(k+1)}{R_y(k+1)}\right)+\varsigma(k) \tag{4}$$

Where, $\varsigma(k)$ is error in the measurement and this error is assumed to be zero mean Gaussian with variance σ^2. The measurement and plant noises are assumed to be uncorrelated to each other. Equation (4) is a nonlinear equation and is linearized using the first term of the Taylor series for R_x and R_y. The measurement relation vector is obtained as:

$$\begin{aligned} H(k+1)=\Big[0 \quad 0 \quad & \hat{R}_y(k+1|k)\big/\hat{R}^2(k+1|k) \\ & -\hat{R}_x(k+1|k)\big/\hat{R}^2(k+1|k)\Big] \end{aligned} \tag{5}$$

Since the true values are not known, the estimated values of R_x and R_y are used in Equation (5). The covariance prediction is given by:

$$P(k+1|k) = \varphi(k+1|k)P(k|k)\varphi^T(k+1|k)+\Gamma Q(k+1)\Gamma^T \tag{6}$$

The Kalman gain is given by:

$$G(k+1)=P(k+1|k)H^T(k+1)[\sigma^2+H(k+1)P(k+1|k)H^T(k+1)]^{-1} \tag{7}$$

The state and its covariance corrections are given by:

$$X(k+1|k+1)=X(k+1|k)+G(k+1)[B_m(k+1)-h(k+1, X(k+1|k))] \tag{8}$$

Where, $h(k+1,X(k+1|k))$ is the bearing using predicted estimate at time index $k+1$:

$$\begin{aligned} P(k+1|k+1)=&[I - G(k+1)g(B_m(k+1), X(k+1|k))]P(k+1|k) \\ &[I-G(k+1)g(B_m(k+1), X(k+1|k))]^T + \sigma^2 G(k+1)G^T(k+1) \end{aligned} \tag{9}$$

Where, g (.) is modified gain function [2]. g is given by,

$$\begin{aligned} g=\Big[0 \quad 0 \quad & \cos B_m \big/ \left(\hat{R}_x \sin B_m+\hat{R}_y \cos B_m\right) \\ & -\sin B_m \big/ \left(\hat{R}_x \sin B_m+\hat{R}_y \cos B_m\right)\Big] \end{aligned} \tag{10}$$

Since the true bearing is not available in practice, it is replaced by the measured bearing to compute the function g (.).

PMMGBEKF

The basic idea is to use a number of independent MGBEKF trackers in parallel, each with a different initial estimate. To do so, the range, course, and speed interval of interest are divided into a number of sub-intervals following geometric progression and each sub-interval is dealt with an independent MGBEKF. Let the range, course, and speed intervals of interest are $range_{min}$, $range_{max}$; $course_{min}$, $course_{max}$; $speed_{min}$, $speed_{max}$, respectively [10].

If hardware support for sufficient computation capacity is available, the size of the sub-intervals can be increased as much as possible to improve the accuracy of the estimated target motion parameters. The initial weight of each MGBEKF is set to $1/N$. Subsequently, the weight of filter i at time k is given by:

$$\omega^i(k)=\frac{p\left(B(k)|i\right)\omega^i(k-1)}{\sum_{j=1}^{N} p\left(B(k)|j\right)\omega^j(k-1)} \tag{11}$$

Where, $p(B(k)|i)$ is the likelihood of the measurement $B(k)$.

Assuming Gaussian statistics, the likelihood $p(B(k)|i)$ can be computed as:

$$p\left(B(k)|i\right)=\frac{1}{\sqrt{2\pi\sigma_{inv}^{i2}}}\exp\left[-\frac{1}{2}\left(\frac{B(k)-\hat{B}^i(k|k-1)}{\sigma^i_{inv}}\right)^2\right] \tag{12}$$

Where, $\hat{B}^i(k|k-1)$ is the predicted angle at k for filter i and ${\sigma^i_{inv}}^2$ is the innovation variance for filter i and it is given by:

$${\sigma^i_{inv}}^2=\hat{H}^i(k)P^i(k|k-1)\hat{H}^{iT}(k)+\sigma^2 \tag{13}$$

The combined estimate of PMMGBEKF is computed using the Gaussian mixture formulas.

SIMULATION AND RESULTS

The algorithm is realized using Matlab on a personal computer. The simulator is developed to create target, ownship and measurements. Target and ownship movements are updated at every 1 second. All 1 second samples are corrupted by additive zero mean Gaussian noise of 2° rms. An EW receiver system is assumed to be intercepting the active measurements generated by radar on a target ship. Ownship is assumed to be carrying out S-maneuver on line of sight (LOS) at a constant speed of 10.3 m/s with turning rate of 1°/s as shown in Fig. 1. In the simulation, all angles are considered with respect Y-axis, 0-360°, and clockwise positive. The ownship moves initially at 90° for a duration 2 minutes and then it changes its course to 270°. Subsequently at 19th, 16th, and 23rd minutes, the ownship changes its course from 270° to 90°, 90° to 270°, and 270° to 90°, respectively. Extensive simulation is carried out and for the purpose of presentation, two scenarios as shown in Table 1 are chosen for evaluation of the algorithm. In the first and second scenarios, target is assumed to be stationary and moving at a speed 15.45 m/s, respectively. Same algorithm is used to track a moving or stationary target. The target is assumed to be using radars with six types of scanning rates. Five radars with the measurement interval 1, 2, 3, 4, and 5 seconds, respectively, assumed to be operating one at a time for 240 seconds each. The simulation is carried out for 1800 seconds. The sixth radar with the measurement interval of 6 seconds is assumed to be operating for the remaining period of 600 seconds.

Performance of MGBEKF algorithm

To start with simulation, the performance of MGBEKF algorithm is evaluated using the two scenarios as shown in Table 1. The initial estimate of target state vector is chosen as follows. As only bearing measurements are available, it is not possible to guess the velocity components of the target. Hence, these components are each assumed as 10 m/s, which are close to the realistic speeds of the vehicles on seawaters. The sonar range of the day, say 25 km,

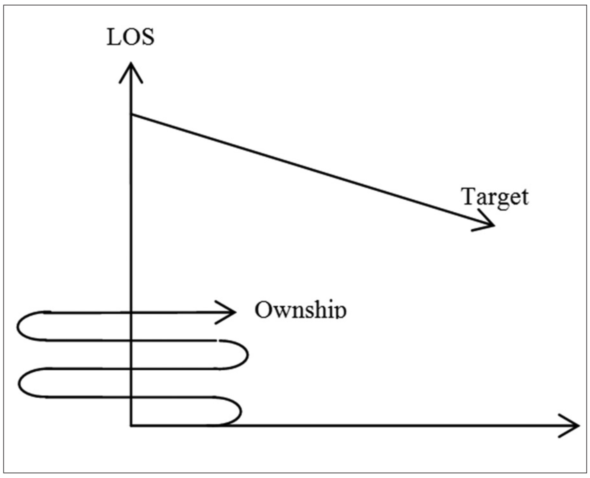

Fig. 1: Ownship in S-maneuver on line of sight

Table 1: Scenarios chosen for evaluation of the algorithm

S.No.	Parameters	Scenario 1	Scenario 2
1.	Initial range (m)	18,520	40,000
2.	Initial bearing (°)	210	210
3.	Target speed (m/s)	0	15.45
4.	Target course (°)	45	45
5.	Ownship speed (m/s)	10.3	10.3
6.	Rms error in bearing (°)	2	2

is utilized in the initialization of target state vector components as follows:

$$X(0|0) = \begin{bmatrix} 10 & 10 & 25000\sin B_m & 25000\cos B_m \end{bmatrix}^T \quad (14)$$

It is assumed that initial X(0|0) is uniformly distributed. Accordingly, the elements of initial covariance are a diagonal matrix and are given by:

$$P_{00}(0|0) = \frac{4\dot{x}^2(0|0)}{12},\ P_{11}(0|0) = \frac{4\dot{y}^2(0|0)}{12},\ P_{22}(0|0) = \frac{4R_x^2(0|0)}{12},$$
$$P_{33}(0|0) = \frac{4R_y^2(0|0)}{12} \quad (15)$$

It is assumed that the errors allowed in the estimated target motion parameters are 20% in range, 10° in course and 20% in speed. The details about the convergence of range, course, and speed estimates obtained with required accuracies are shown in Table 2. The results are shown in Figs. 2 and 3 with identification MGBEKF using initialization 1 "MGBEKF Init 1." It is observed from the results that the convergence of the solution for the scenario 1, which describes a stationary target, is not satisfactory. The initialization of target state vector is modified slightly as follows to track a stationary target as follows.

$$X(0|0) = \begin{bmatrix} 0.1 & 0.1 & 25000\sin B_m & 25000\cos B_m \end{bmatrix}^T$$

With this modification, the convergence of the solution for scenario 1 is satisfactory but not satisfactory for scenario 2 as shown in Figs. 2 and 3 with identification "MGBEKF Init 2." From this simulation, it is understood the time to obtain the convergence of the solution is highly dependent on the values used for initialization of target state vector components, as shown in Table 2.

Simulation of PMMGBEKF algorithm

In this section, the performance of PMMGBEKF algorithm is evaluated using two scenarios shown in Table 2. In simulation, $range_{min}$, $range_{max}$; $course_{min}$, $course_{max}$; $speed_{min}$, $speed_{max}$ are considered as 5000 m, 40,000 m; 0°, 359°; 0 m/s, 20 m/s, respectively. The numbers of elements in each subinterval are considered as 10, resulting the number of filters 1000. The results obtained in simulation are shown in Figs. 2 and 3 with identification of "Parameterized." It is observed that range, course, and speed estimates with required accuracies are obtained and the details about the convergence of the solution are shown in Table 2. PMGBEKF is able to track stationary or moving target satisfactory.

From Tables 2 and 3, it is understood that inclusion of parameterization reduces the time to obtain convergence of the solution when compared to that without parameterization (i.e., with single MGBEKF algorithm).

Limitations of the algorithm

Angle on target bow (ATB) is the angle between the target course and LOS. When, ATB is more than 60°, the distance between the target and ownship increases as time increases, and the bearing rate decreases substantially with the increase in number of samples. In such situation, it is very difficult to track the target. Furthermore, the algorithm cannot provide good results when the measurement noise is more than 2° rms. In general, these two situations are constraints to any type of filtering technique.

CONCLUSION

In this application of passive ship target tracking, prior knowledge of target range, course, or speed is not available. Time to obtain convergence greatly depends on the initialization of the target state vector. Parameterization in initialization of MGBEKF state vector is included to reduce the dependency of the convergence

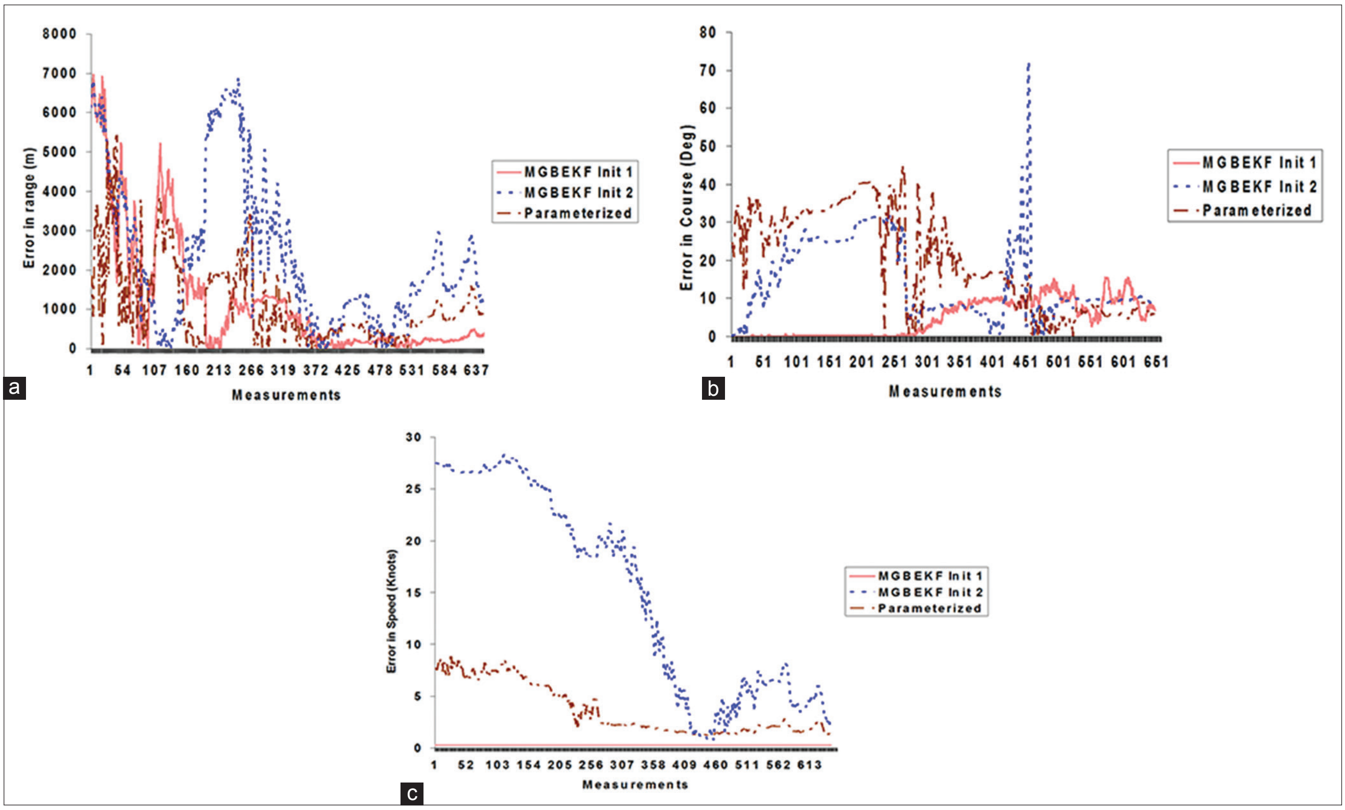

Fig. 2: Error in estimates for scenario 1. (a) Range, (b) course, (c) speed

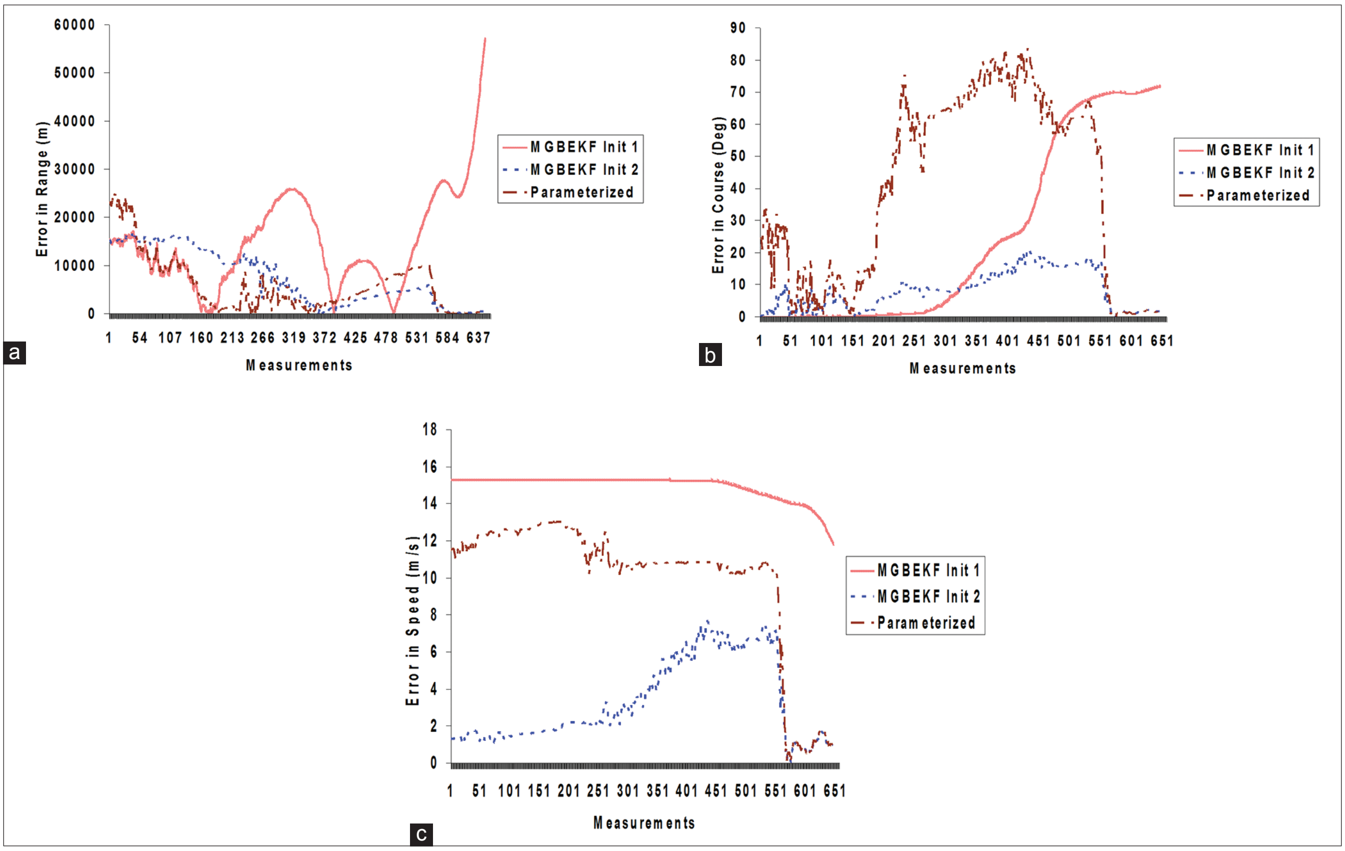

Fig. 3: Error in estimates for scenario 2. (a) Range, (b) course, (c) speed

Table 2: Convergence time (in seconds) with single MGBEKF

Scenario	Convergence time (in seconds)					
	Using $\begin{bmatrix}\dot{X} & \dot{Y}\end{bmatrix} = \begin{bmatrix}0.1 & 0.1\end{bmatrix}$			Using $\begin{bmatrix}\dot{X} & \dot{Y}\end{bmatrix} = \begin{bmatrix}10 & 10\end{bmatrix}$		
	For range estimation	For course estimation	For speed estimation	For range estimation	For course estimation	For speed estimation
1	137	1095	2	292	Not converged	1729
2	Not converged	Not converged	Not converged	1225	1228	1323

MGBEKF: Modified gain bearings-just extended Kalman filter

Table 3: Convergence time (in seconds) with parameterization

Scenario	Convergence time (in seconds) with PMMGBEKF		
	For range estimation	For course estimation	For speed estimation
1	281	737	477
2	1158	1165	1292

PMGBEKF: Parameterization modified gain bearings-just extended Kalman filter

time on initialization. From the results obtained in simulation, PMGBEKF is recommended to track the target using ESM bearing measurements.

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