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Analysis of Target Location Estimation in High Performance Radar System

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Abstract—In this paper, an analysis of a target location estimation system using the best linear unbiased estimator (BLUE) for high performance radar systems is presented. In synthetic environments, we are here concerned with three key elements of radar system modeling, which makes radar systems operates accurately in strategic situation in virtual ground. Radar Cross Section (RCS) modeling is used to determine the actual amount of electromagnetic waves that are reflected from a tactical object. Pattern Propagation Factor (PPF) is an attenuation coefficient of the radar equation that contains the reflection from the surface of the earth, the diffraction, the refraction and scattering by the atmospheric environment. Clutter is the unwanted echoes of electronic systems. For the data fusion of output results from radar detection in synthetic environment, BLUE is used and compared with the mean values of each simulation results. Simulation results demonstrate the performance of the radar system.

Keywords—Best linear unbiased estimator (BLUE) , data fusion, radar system modeling, target location estimation

I. Introduction

IN synthetic environments, estimation of moving targets has been investigated. To achieve exact target location, radar system modeling and the BLUE technique, which is a kind of data fusion are used in this paper. Radar system modeling factors are divided into RCS modeling, PPF modeling, and clutter modeling. Target reflectivity, in which the radar system uses information extracted from a tactical object's surface in terms of electromagnetic wave-material interaction, is considered in the radar equation as a parameter that is called RCS [3]. Also, rain attenuation, which will be considered in PPF, and clutter modeling, are parameters that help to determine the reliability of a radar system [2]. As an evolving technology, multisensor data fusion is also important in representing tactical situation in synthetic environments [1]. The core of the problem is how to fuse data to create an accurate estimation of tactical targets [4]. BLUE, a method of data fusion in distributed wireless sensor networks, is considered in this paper as a method to estimate a target's location more accurately.

In this paper, we design a radar system to represent accurate target location using those factors and to simulate a designed radar system in order to obtain high performance results for target location estimation using BLUE. To observe the performance of BLUE from a point of view of data fusion, the average received data will be compared with computer simulations.

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II. Radar System Modeling

In general, range, azimuth and elevation angle are basic measurements for achieving target location. But, in synthetic environments, realistic sensing data is the key to achieving precise measurements of tactical target location using radar systems. In realistic environments, there exist many parameters, including environmental parameters, radar parameters, noise, and clutter. These parameters have effects as disturbances or jamming elements. Thus, additional modeling that can consider environmental parameters is important in the design of high performance radar systems. This section describes RCS modeling, PPF modeling, and Clutter modeling, all of which are related to the environmental parameters, as stated above.

A. RCS Modeling

RCS, which is an abbreviation of radar cross section, is a unit of area (for example, square meters) and is a measure of the energy redirected by the target back in the direction of the radar [5]. It is denoted by σ in the radar equation and is determined by the size and physical properties of target and by the viewing angle of the radar. Suppose the size of the target becomes larger without changing any of the other conditions: RCS should be larger because the redirected area is larger. Even when two tactical targets have the same redirected area, they can have different RCS values according to the physical properties of the targets. For example, a target that is covered with radar absorbing material has a smaller RCS than other targets. Finally, the radar's viewing angle is one of the parameters determining the RCS. A point that scatters electromagnetic waves from the target is called a scattering point; all objects have infinite scattering points. By the infinite scattered waves from those points, radar detects the sum of the waves with constructive and destructive interference. Thus, the phase of a scattered wave that determines the target's shape, frequency, and radar viewing angle changes the RCS.

For RCS modeling, methods of making a database to consist of real tactical target RCS data can be classified into two types depends on the database size. One is the single RCS model, which provides a single RCS value for each tactical object. Using this model, it is possible to reduce the size of a database, but it is hard to present complex surfaces and physical properties, which change the RCS rapidly. Providing a physical RCS model is the other method. In this case, we can use precise model of the tactical object and obtain a variant RCS according to the changes of the radar's viewing angle. This latter method can be an accurate RCS modeling method, but does require a larger database. Thus, users apply an adequate RCS model after considering the properties of the tactical object.

B. PPF Modeling

In reality, electromagnetic waves do not radiate in free space; there are differences when transmitting radio waves in compliance with radar systems that transmit electromagnetic waves for hundreds of kilometers. Examples of differences are reflection from the earth's surface, diffraction, refraction and scattering in the atmosphere. PPF is given below.

$$PPF = \{1 + \rho^2 + 2\rho \cos(\frac{4\pi h_r \theta_t}{\lambda} + \phi)\}^2, \tag{1}$$

where PPF is the pattern propagation factor that is described as above, ρ and ϕ are the norm and the phase of total reflection coefficient, respectively; ϕ is the phase of total reflection, h_r is the height of the antenna, θ_t is the elevation angle of the target, and λ is the wavelength, which is determined by the radar's nominal frequency.

Also, PPF considers those factors and applies them as an attenuation coefficient in the radar equation, as follows:

$$P_e = \frac{P_s \cdot G^2 \cdot \sigma \cdot \lambda^2 \cdot (PPF)^2}{(4\pi)^3 \cdot R^4}, \tag{2}$$

where P_e and P_s are transmit power and received power, respectively. G is an antenna of gain, σ is the RCS of the target, λ is the transmitted wave length, PPF is the pattern propagation factor, and R is the distance between radar and target.

C. Clutter Modeling

In the operation of a radar system, clutter is the unwanted echoes that radiate reflected radio waves from non-target objects. In the case of weather radar, the tactical object will be clutter. Otherwise, weather targets are detected as clutter when a radar which want to detect tactical objects and estimates target's location. In reality, clutter, such as wave height, wind direction, antenna height, rainfall, snowfall and fog affect the radar system as a kind of noise. Those kinds of clutters are divided into two types. One is surface clutter, which contains land and sea clutter; the other, which is called volume clutter, is reflected from weather targets.

Surface clutter is modeled using the RCS values of the main lobe beam's clutter and side lobe beam's clutter, as below:

$$\sigma_{SC} = \frac{\sigma_{MBc} + \sigma_{SLc}}{1 + (\frac{R}{R_g})^4}, \tag{3}$$

where σ_{SC} is the RCS of surface clutter, σ_{MBc} is the RCS of main lobe beam clutter, σ_{SLc} is the side lobe beam clutter, R is the distance between the target and the antenna, and R_g is the distance between the unwanted target and the antenna. Applying those factors, we can design surface clutter RCS in equation (3) and obtain the power of surface clutter.

$$P_{sc} = \frac{P_t \cdot G_a^2 \cdot G_{comp} \cdot G_{STC} \cdot \lambda^2 \cdot \sigma_{SC} \cdot (PPF)^2}{(4\pi)^3 \cdot R_d^4 \cdot L_{sys} \cdot L_{beamshape}^2 \cdot L_{rain}^2}, \tag{4}$$

where P_{sc} is the power of surface clutter, P_t is the transmit power, and G_a, G_{comp} and G_{STC} are the antenna gain, pulse compression gain and sensitivity time control (STC) gain, respectively; λ is the wavelength of the radio waves, σ_{SC} is the RCS of the surface clutter, R_d is the distance between the antenna and the target, and L_{sys}, $L_{beamshape}$ and L_{rain} are system loss, beam shape loss and rainfall attenuation respectively. These variables are described in [5].

On the other hand, volume clutter is determined by rainfall and snowfall, which create the performance difference. We apply those values as parameters in computing the power of the volume clutter as follows:

$$P_{vc} = \frac{\kappa_1 \cdot P_s \cdot G \cdot \tau \cdot Z}{R^2 \cdot \lambda^2}, \tag{5}$$

where κ_1 is a constant with a value of 1.2×10^{-10}, P_s is the maximum power of the signal, G is the antenna gain, τ is the pulse duration, Z is a parameter of reflection that depends on rainfall condition, R is the distance between an antenna and a target, and λ is the wavelength of the radio waves.

Considering the power of clutter, it can be an index of determining a threshold of target detection level; this is called signal-to-clutter ratio (SCNR), and is given as below:

$$SCNR = \frac{P_s}{P_{sc} + P_{vc} + P_n}, \tag{6}$$

where P_{sc} is the power of surface clutter, P_{vc} is the power of volume clutter, and P_n is the noise power. In reality, clutter elements have more impact on detecting targets than noise.

III. Target Location Estimation

To estimate the position of a target exactly, we applied BLUE for the data fusion technique which is given by [6]. Let x_k be observations from K independent sensor systems. The observations obey the model

$$x_k = \phi_k(\theta) + w_k, \quad k = 1, ..., K, \tag{7}$$

where $\phi_k : \mathbf{R}^p \to \mathbf{R}$ is a nonlinear function with the noise term w_k, θ is a $p \times 1$ vector parameter that we want to estimate and that will be considered as scalar in this case, and k is a zero-mean independent random variable with variance σ_k^2. In a local compression stage, sensor systems perform local quantization and send the results of local quantization to the data fusion center. If infinite bandwidth were available, the input to the data fusion center would be considered as the observations x_k. Under this condition, an optimal estimate $\hat{\theta_0}$ could be generated by a data fusion technique that is called BLUE, as below:

$$\hat{\theta_0} = \hat{\theta}_{BLUE} := (\sum_{k=1}^{K} \frac{x_k}{\sigma_k^2})(\sum_{k=1}^{K} \frac{1}{\sigma_k^2})^{-1}, \tag{8}$$

that has the minimum mean-square error among all linear unbiased estimators.

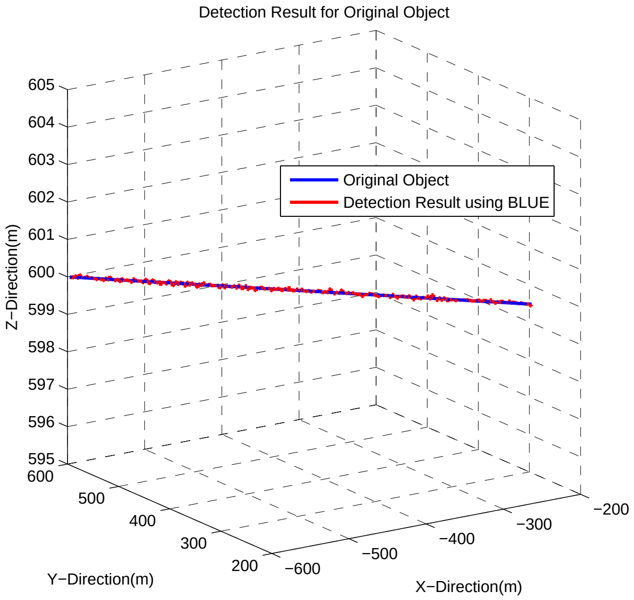

Fig. 1. The trajectory of estimated target location using BLUE technique.

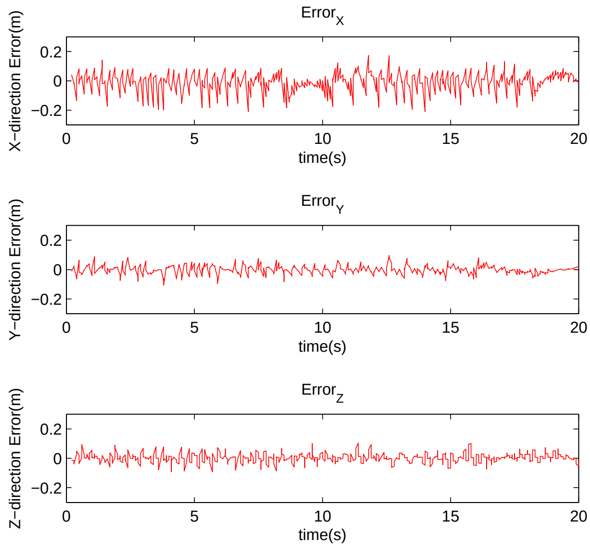

Fig. 2. Distance between the estimated target location using the BLUE technique and the position of the original tactical object in an orthogonal coordinates.

IV. Simulation Results

In this section, we simulated a high performance radar system with a target detection scenario that is based on section II. This scenario has three detection radars and one target airplane; all of the objects are in motion and are described in Table I. Also, the initial positions of the tactical objects are described in Table II.

Figure 1 shows the trajectory of the estimated target location using the BLUE technique, which is very close to the original tactical object's trajectory. To observe the difference between the two trajectories, we use the error term, which is defined as follows:

TABLE I
Basic Motion

	Angle(Degree)	Speed(knot)
Target Airplane	-45	50
Radar 1	0	0
Radar 2	-30	30
Radar 3	-135	20

TABLE II
Initial Position of Tactical Objects

	X-axis(m)	Y-axis(m)	Z-axis(m)
Target Airplane	-600	600	600
Radar 1	0	-1500	0
Radar 2	600	200	0
Radar 3	1000	600	0

$$ERROR_X = X_{BLUE} - X_{Ori}, \tag{9}$$

$$ERROR_Y = Y_{BLUE} - Y_{Ori}, \tag{10}$$

$$ERROR_Z = Z_{BLUE} - Z_{Ori}, \tag{11}$$

where X_{BLUE}, Y_{BLUE}, and Z_{BLUE} indicate the estimated target location using the BLUE technique in an orthogonal coordinates system, and X_{Ori}, Y_{Ori}, and Z_{Ori} indicate the position of the original tactical object. For each coordinate, $ERROR_X$, $ERROR_Y$, and $ERROR_Z$ are described in the Fig. 2.

The distance between the original position and the estimated target location is less than 0.2m, as shown in Fig. 2. Comparison with the distance to the tactical object, the total of $ERROR_X$, $ERROR_Y$, and $ERROR_Z$ is very small. To evaluate BLUE in detail, we compare the ratio of the error size between the BLUE technique and the mean value for detected data which is denoted as ER_X, ER_Y, and ER_Z in this paper.

$$ER_X = \frac{||ERROR_X||}{||(\sum_{k=1}^{N} \frac{(X_k - \mu_X)}{N})||}, \tag{12}$$

$$ER_Y = \frac{||ERROR_Y||}{||(\sum_{k=1}^{N} \frac{(Y_k - \mu_Y)}{N})||}, \tag{13}$$

$$ER_Z = \frac{||ERROR_Z||}{||(\sum_{k=1}^{N} \frac{(Z_k - \mu_Z)}{N})||}, \tag{14}$$

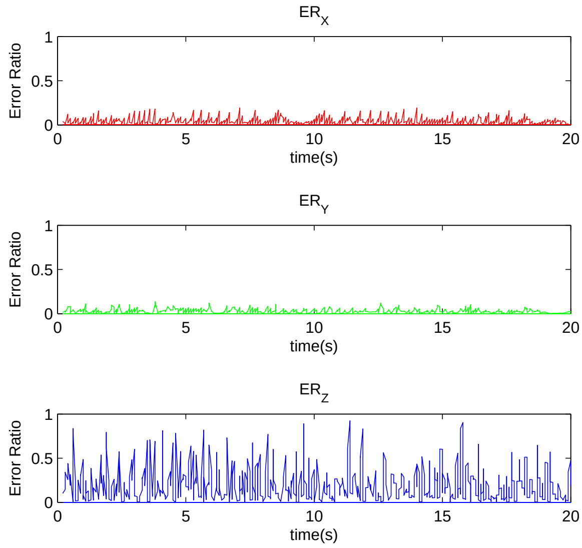

Fig. 3. The ratio of the error size of the BLUE technique to the mean value for detected data in an orthogonal coordinates system.

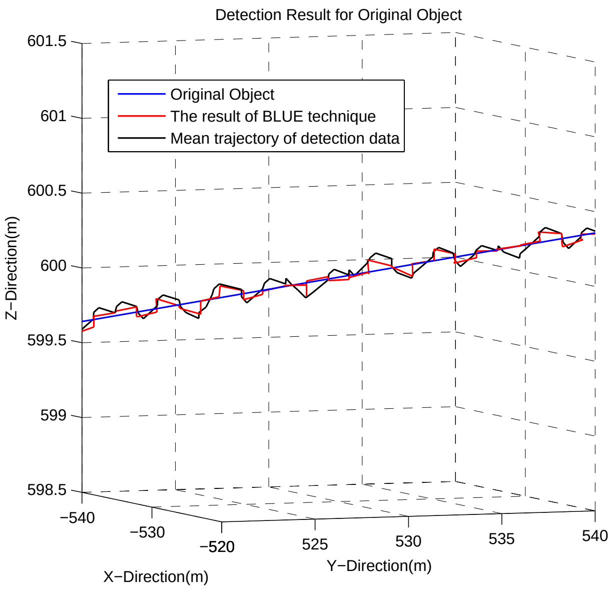

Fig. 4. A partially expanded trajectory for original object, the result of BLUE technique and mean trajectory of detection data.

where X_k, Y_k, and Z_k indicate the detected position in each coordinate for the k-th radar system, and μ_X, μ_Y, and μ_Z are the average position of the result of detection. After computing ER_X, ER_Y, and ER_Z, the simulated result is shown in Fig. 3.

In this figure, we can observe that ER_X, ER_Y, and ER_Z are less than 1, which means that the BLUE technique for data fusion in target location estimation is better than the mean value of all the detected data. It is possible to see a more accurate target location estimation result in the Fig. 4. This figure is a partially expanded graph using the data from Fig. 1 to observe the trajectories in detail.

V. Conclusions

We investigated radar modeling techniques and data fusion to estimate target location accurately. Considering radar modeling elements such as RCS, PPF, and clutter, a radar system operates more accurately in a synthetic environment. BLUE is a data fusion technique for target location estimation; in this paper, the simulation results show high performance for the estimation of a tactical object's location.

Acknowledgments

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