



Track Generation and Management Within ACES

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This article describes the radar modeling methods used for Tactical Ballistic Missile track generation and management currently implemented in the APL Coordinated Engagement Simulation (ACES). The ACES radar model generates radar tracks unique to each radar platform, consequently affecting the accuracy of the integrated track picture at each platform and the effectiveness of coordinated engagements. Modeling fidelity is chosen to provide flexibility to represent various radar types and functionality while maintaining reasonable execution times to support Monte Carlo analyses. The complexity of the radar modeling will increase as ACES grows to support other missions.

INTRODUCTION

The APL Coordinated Engagement Simulation (ACES) is being created to evaluate and develop distributed weapons coordination methods for supporting Navy, Joint, and Allied area and theater Tactical Ballistic Missile Defense (TBMD), Overland Cruise Missile Defense (OCMD), and self-defense and area defense Anti-Air Warfare (AAW). An analysis of the effectiveness of the different distributed weapons coordination approaches to achieve force-level coordination must consider critical factors that affect the outcome of processes throughout the detect-to-engage chain of events. In operational situations these processes are fundamentally dependent on available track information. For a given unit, track information may be generated locally or obtained from other units via common networks. Therefore, the generation of a realistic representation of the air picture at the individual platform level has been a primary objective in the development of ACES.

The ACES radar model generates radar tracks unique to each sensor, thereby impacting the accuracy of the integrated track pictures and the effectiveness of coordinated engagements. Modeling fidelity is chosen to provide realistic radar track errors while maintaining reasonable execution times to support Monte Carlo analyses. ACES uses a generic radar detection model (RDM) designed to provide flexibility to model various types of radars. The RDM applies fundamental radar equations and modeling methods that depend on parameters unique to the specific radars being modeled. In conjunction with environmental and target characteristics, the RDM is used to determine the radar's view of the world. It is a piece of the overall track generation and management modeling within ACES. Other key elements include the selection of waveforms to manage radar resources during search and track, the combination of detections to form tracks, the clustering of

ballistic object tracks, and the correlation of local tracks to remote tracks to form a unit-level integrated air picture. These supporting pieces are more unique to the specific radar platforms modeled. This article focuses first on the approach taken to model a generic phased array radar on a stationary platform to support TBMD. Subsequent sections address processes that have been implemented for clustering, correlating, and extrapolating ballistic tracks.

GENERIC RADAR DETECTION MODEL

The generic RDM calculates the returned signal-to-noise ratio (SNR) and associated probability of detection based on radar, target, and environmental characteristics provided by input files. Figure 1 lists the RDM inputs, which are used to calculate the SNR of a single pulse as follows:

$$\text{SNR} = \frac{P_t G_t G_r \lambda^2 \sigma F^4 \tau}{(4\pi)^3 R^4 L k T_0 F_n}, \quad (1)$$

where

- P_t = peak power of the transmitter,
- G_t = transmitter gain,
- G_r = receiver gain,
- λ = wavelength of the transmitted pulse,
- σ = target radar cross-section (RCS),
- F = propagation factor,
- τ = pulse width,
- R = range to target,
- L = system losses,
- k = Boltzmann's constant,
- T_0 = standard temperature, and
- F_n = receiver noise figure.

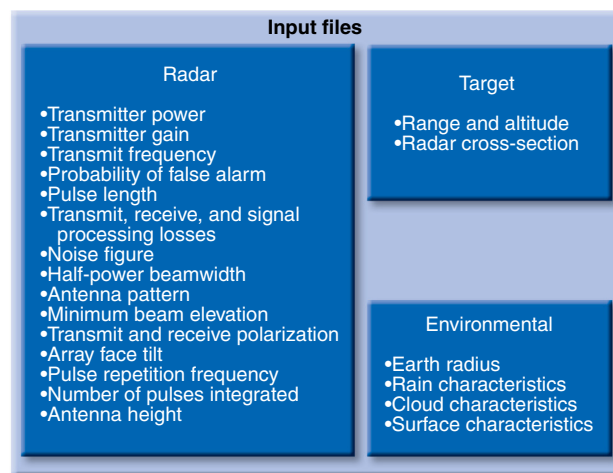


Figure 1. Radar detection model inputs.

System losses L include losses from the transmitter and receiver, signal processing, and scalloping and scanning. Scalloping and scanning losses are associated with a phased array radar. Scalloping losses are the average losses due to the target not always being in the center of the beam detecting the target during search. Scanning losses are due to the beam being off the normal of the array face. Both can be provided as input tables of elevation- and/or azimuth-dependent average losses. If these data are not available (e.g., when evaluating foreign systems), generic equations can be used to approximate them.

The propagation factor F accounts for the attenuation due to atmospheric gases, rain, clouds, multipath, and diffraction. Atmospheric attenuation computations gradually reduce the attenuation at extreme altitudes to account for the thinning atmosphere. This approach was selected because the RDM is used to track high-altitude TBMs. The multipath calculations only account for specular reflections. Although diffuse reflections predominate over rough surfaces, multipath nulls are more severe over smooth surfaces where specular reflections predominate.

The APL Tropospheric Electromagnetic Parabolic Equation Routine (TEMPER) is commonly used to calculate multipath and diffraction effects for high-fidelity models. Because of TEMPER's long run time, higher-fidelity radar models use look-up tables to access the propagation effects calculated by it. Each output of TEMPER is specific to a particular antenna pattern and antenna orientation. In an ACES scenario, there can be great variability in the types of radars and antenna orientations. Instead of maintaining an ever-changing database of TEMPER results, a simplified method of calculating propagation effects is implemented with multipath, based only on specular reflections and diffraction equations specific to radar frequencies. Comparisons between RDM and TEMPER propagation results and the extremely short run time of the former show that the RDM is appropriate for supporting ACES. Figure 2 illustrates the propagation results of an S-band radar tracking a target flying at a 1-km altitude over a calm sea state and standard atmospheric conditions.

Limitations do exist in the RDM. Clutter computations are not included because the radar platform is assumed to be stationary and using pulse Doppler radar or moving target indicator processing, and the target's background clutter is assumed to be negligible. These assumptions may not be particularly limiting when the targets being considered are at high altitudes and high velocities, such as TBMs. However, the addition of clutter computations and moving target indicator modeling is planned as the simulation evolves to support AAW and OCMD. The RDM also assumes a standard atmospheric condition, so modeling ducting environments will require changes. If the need to implement

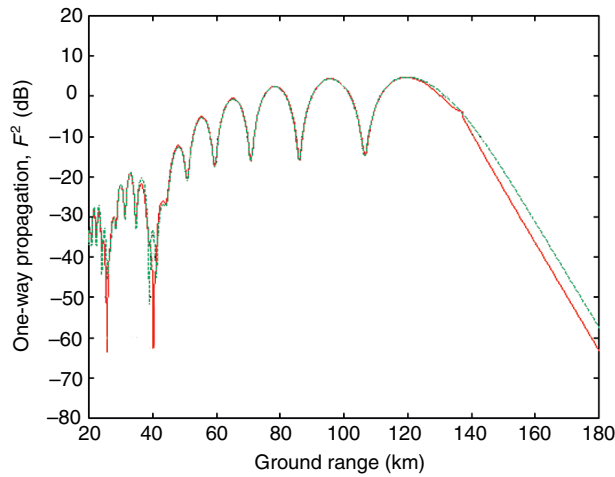


Figure 2. Comparison of RDM (red) and TEMPER (green) propagation effects.

this capability arises, the use of a database of TEMPER outputs or the application of simplified ray tracing techniques will be investigated.

SEARCH-TO-TRACK INITIATION

ACES uses the APL-developed Array Radar Guaranteed Useful Search tool to generate search sectors. Unlike in AAW, full hemispherical search for TBMD does not produce adequate probabilities of detection at the required detection ranges owing to constrained radar resources. The goal of constructing area defense search sectors is to detect TBMs early enough to complete minimum reaction time engagements for intercepts at specific altitudes. Inputs to the Array Radar Guaranteed Useful Search include suspected TBM launch zones, TBM types, assigned defended assets, and ship location. The resulting search sectors include elevation- and azimuth-specific waveforms, slant range limits, and slant range rate limits as a function of beam positions.

Each radar has a search sector revisit rate assigned to each of its search sectors. This rate is based on radar resources available or a specified input value. Every time the simulation steps forward in time, each target is checked to determine if it is present in the search volume. If multiple targets are present, they are checked for resolvability. The target resolution process considers azimuth, elevation, range, and Doppler resolutions. If targets are not resolvable, the root mean square of the RCS of the unresolved targets is used by the RDM. The search sector is used to select the waveform of the search beam closest to the target's location. The waveform provides the pulse length and number of pulses to integrate. The average scalloping loss is determined based on the azimuth and elevation of the target. The angular distance between the beam center and the location of the target can be used to calculate a more

accurate scalloping loss than the average scalloping loss data, but this requires significantly more processing time. The RDM calculates the integrated SNR using the RCS of the target. It uses a roll-averaged, aspect-dependent RCS and treats this as the median value for a Swerling IV distribution. Finally, look-up tables are used to determine the probability of detection based on the integrated SNR and the desired probability of false alarm.

The actual position of the active search beam during a search volume update is not modeled over time. To approximate the variability of when the target position coincides with an active beam searching near the target, the probability of detection is calculated once per second and modified using

$$P_D' = \frac{1}{k} \cdot P_D, \quad (2)$$

where P_D' is the modified probability of detection, k is the number of seconds required to search the entire search volume, and P_D is the currently calculated probability of detection using the nearest beam in the search lattice. The $1/k$ factor produces a uniform likelihood of the active beam being the one used to calculate the probability of detection. Later versions will model the actual beam positions over time.

After the target is detected during search, the process of initiating a track is based on a required number of detections out of a specific number of attempts defined by the type of radar platform. The SNR is assumed constant throughout this process so that the probability of initiating the track can be simplified and quickly calculated. Equation 3 shows the probability of initiating a track for a simple case where the track initiation requires at least M detections out of N attempts:

$$P_{\text{MotN}} = \sum_{i=M}^N \binom{N}{i} \cdot P_D^i \cdot (1 - P_D)^{N-i}. \quad (3)$$

If the track initiation succeeds, then track initiation time is approximated as the detection time plus N times the track initiation update rate. This method is appropriate because the target RCS used in the SNR calculation is representative of a range of orientations and the target does not move far during the track initiation process.

RADAR MANAGEMENT

During track, the generic shipboard phased array radar selects waveforms to maintain the returned SNR within a desired range. The selection logic uses a maximum and minimum SNR, a preferred SNR, and a table of available waveforms for the radar. The available waveforms are of varying sizes in terms of number

of pulses and pulse lengths. When the SNR exceeds the maximum bound, a shorter waveform is selected for the next update so that the resultant SNR will be closer to the preferred SNR. Conversely, when the SNR drops below the minimum SNR, a longer waveform is selected for the next update. A rolling average SNR is compared to the SNR bounds instead of the instantaneous SNR to inhibit overreaction to orientation-based RCS fluctuations of the target. The number of returns to be considered in the rolling average can be adjusted for the particular radar. The purpose of adjusting the waveform is to minimize its size while maintaining a good-quality track, thus conserving radar resources.

The radar is limited in radar resources based on allowing time for the transmitter to transmit a signal, waiting for the reflected signal to return from the target or from the region of interest, allowing the receiver to process the signal, waiting for energy to be available to send the next signal, and maintaining radar component temperatures within permissible bounds. Based on the events in the scenario, prioritization of the radar activities can cause certain activities to be delayed or abandoned. Activities that are currently prioritized by the radar are

- Search sector revisit
- Cued search
- Transition to track
- Track management
- Missile communication
- Discrimination
- Kill assessment

Each radar platform prioritizes these activities differently depending on its mission.

The radar resources are accounted for by calculating the percentage of time devoted to a particular activity so that the sum of percentages is limited to 100%. The following equations show how this percentage is calculated per activity:

$$\%R = [n\tau + (n - 1)(y + q)]UR, \quad (4)$$

$$y = \max \left[\left(\frac{2R}{c} + z \right), \left(\frac{1}{f_p} - \tau \right) \right], \quad (5)$$

$$q = \max \left[\left(\frac{2R}{c} + w \right), \left(\frac{1}{f_p} - \tau \right) \right], \quad (6)$$

where

- %R = percentage of time devoted to the particular activity,
- n = number of pulses in the waveform associated with the activity,

- τ = pulse length in seconds,
- y = delay between pulses within a waveform in seconds,
- q = delay between waveforms in seconds,
- UR = update rate in hertz,
- R = maximum range associated with the activity,
- z = processing delays between pulses,
- w = processing delays between waveforms, and
- f_p = pulse repetition frequency.

The variables y and q represent, respectively, the maximum delay for the transmitter to maintain component temperatures within permissible bounds and the amount of time it takes the pulse or waveform to reach the region of interest and return to the receiver.

LOCAL TRACK ERRORS

Once the target is in track, the accuracies of the track state are based on the SNR return. The following equations are used to calculate the range, angular (either azimuth or elevation), and velocity standard deviations of error for an individual raw detection:

$$\sigma_{\text{Range}} = \frac{\text{Range Resolution}}{k_R \sqrt{2\text{SNR}_1 n}}, \quad (7)$$

$$\sigma_{\text{Angular}} = \frac{\text{Angular Resolution}}{k_\theta \sqrt{2\text{SNR}_1 n}}, \quad (8)$$

$$\sigma_{\text{Velocity}} = \frac{\sigma_{\text{ECEFRaw}}}{k_V}, \quad (9)$$

where k_R , k_θ , and k_V are constants associated with the measurement processes; n is the number of pulses; and σ_{ECEFRaw} is the Earth-centered, Earth-fixed (ECEF) x, y, or z standard deviation of error derived from a coordinate transformation of the raw range and angular standard deviation of error.

A generic approach is used to manipulate these raw standard deviations of error to approximate the effects of filtering and to approximate a variety of track filters; errors are easily parameterized to evaluate their effect on the performance of coordinated engagements. However, specific filter algorithms can be implemented if that level of fidelity is desired. The generic approach uses the following equations to approximate the standard deviations of error after track filtering:

$$\sigma_{\text{Track}}(N = 1) = \sigma_{\text{ECEFRaw}}, \quad (10)$$

$$\bar{\sigma}_N = \sqrt{\bar{\sigma}_{N-1}^2 + \frac{(\sigma_{\text{ECEFRaw}}^2 - \bar{\sigma}_{N-1}^2)}{N}}, \quad (11)$$

$$\sigma_{\text{Track}}(N) = \frac{\bar{\sigma}_N}{k_{\text{Fa}} \left(\frac{N}{N_{\text{MAX}}} \right)^{k_{\text{Fb}}}}, \quad (12)$$

where

- N = the number of detections of the target,
- $\bar{\sigma}_N$ = a rolling average of the ECEF x , y , or z standard deviation of error,
- N_{MAX} = maximum value N can become, and
- k_{Fa} and k_{Fb} = adjustable filter accuracy parameters.

Each time the target is detected with a track beam, N is incremented up to the maximum N_{MAX} . If the raw standard deviations of error do not dramatically increase, subsequent detections increase N and decrease the standard deviation of error after track filtering, thereby improving track accuracy. Conversely, if detections are not successful, N is decremented, thus increasing the standard deviation of error after track filtering and degrading track accuracy after filtering. During track, ACES determines if a detection is successful by comparing the SNR to a threshold SNR. If the SNR is less than the threshold it counts as a miss, and if it is greater than the threshold it counts as a detection. The parameters for N_{MAX} , k_{Fa} , and k_{Fb} were set in ACES to match the performance from a model using an actual Kalman filter employed for tracking TBMs.

The track measurements are created by randomly drawing from a normal distribution using the calculated ECEF standard deviations of error and the target ECEF ground truth values as the means. This is done for position and velocity components.

Local bias errors are also added to the measurements. The standard deviations of the bias errors can differ among platform types. These biases represent errors in sensor calibration and navigation. At the beginning of the simulation, position and orientation bias errors are randomly drawn for each sensor, and these biases are held constant throughout the scenario. The product of the orientation bias and the range to the target are added to the position bias to obtain the total bias error.

Once the track states are determined, they are linearly extrapolated to decide where to point the next beam to update the track. The angular error between the beam center and the ground truth target position is used to calculate a beampointing loss, which is applied in calculating the updated SNR.

LOCAL TRACK CHARACTERIZATION

In ACES, each platform characterizes local tracks to differentiate tracks on objects associated with TBMs from those on aircraft and to associate TBM objects that are from the same launch event. ACES methodology includes the following processes:

- “Categorize” tracks, i.e., is it a piece of a TBM or an aircraft?
- “Cluster” TBM tracks together.
- Select a primary object track (POT) for each cluster.
- “Link” POTs from the same TBM launch event.
- Select a guidance track for each launch event from among its POTs.

Categorization in ACES is based on elevation, altitude, velocity, and range rate. Tracks that meet specific criteria are designated as TBM tracks. Because multiple objects may be associated with a given TBM launch event, all TBM tracks are subjected to a clustering process. A list of TBM tracks is ranked in decreasing order of mean RCS. The track on the object with the largest RCS becomes the first POT. Other (secondary) tracks are clustered with it based on separation velocity and separation distance tests. The clustered tracks are removed from the list, and the process is repeated as many times as necessary until no tracks remain. Only POTs are made available for engagement decision processes and for reporting to other units.

BALLISTIC EXTRAPOLATION OF LOCAL TRACKS

Local TBM tracks are extrapolated based on Kepler’s laws to support threat assessment and engageability calculations. Because the tracks contain errors, an extrapolated TBM track state creates an error ellipse about a predicted impact point. If this error ellipse breaches the boundaries of a defended asset, the track is declared a threat. The Kepler equations take the position and velocity data of the track and determine the eccentricity vector and the geometric constant of the conic called the *parameter*. These variables allow the position of the ballistic object to be determined anywhere along its elliptic trajectory using

$$r = \frac{p}{1 + e \cdot \cos(\nu)}, \quad (13)$$

where

- r = ECEF position vector of the ballistic object,
- p = the parameter,
- e = eccentricity vector, and
- ν = angle between the position vector and the vector from the prime focus to the periapsis.

Figure 3 provides an illustration. Kepler’s second law states that the line joining the ballistic object and the prime focus sweeps out equal areas in equal times. This law is used to approximate the position of the ballistic object at any time.

By appropriately adding the track’s velocity standard deviations of error to the radar’s measured velocity state, the extreme cross-range and down-range impact

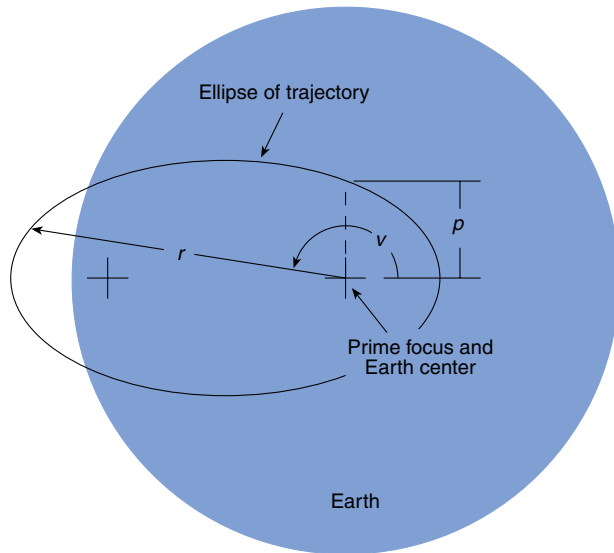


Figure 3. Ellipse of the ballistic trajectory.

locations are determined to define the impact error ellipses associated with the magnitude of standard deviations added. This ellipse is centered about the predicted impact point, which is calculated from the radar's measured velocity state without adding any standard deviations of error.

This approach is appropriate for the extrapolation of ballistic objects over long periods of time, such as predicting impact location and engageability. However, ACES also extrapolates ballistic track states to support correlation. Data with different time stamps are extrapolated to a common time before attempting correlation. Because the duration of these extrapolations is on the order of seconds and that for impact location and engageability can be on the order of minutes, other less accurate methods were investigated to support these extrapolations of shorter durations. One approach was to use constant gravity ballistic equations:

$$\bar{\mathbf{r}}_{\text{coast}} = \bar{\mathbf{r}}_0 + \bar{\mathbf{v}}_0 \cdot t - \mu \cdot \left(\frac{\bar{\mathbf{r}}_0}{r_0^3} \right) \left(\frac{t^2}{2} \right), \tag{14}$$

$$\bar{\mathbf{v}}_{\text{coast}} = \bar{\mathbf{v}}_0 - \mu \cdot \left(\frac{\bar{\mathbf{v}}_0}{r_0^3} \right) t, \tag{15}$$

where

$\bar{\mathbf{r}}_{\text{coast}}$ and $\bar{\mathbf{v}}_{\text{coast}}$ = extrapolated position and velocity vectors, respectively,

$\bar{\mathbf{r}}_0$ and $\bar{\mathbf{v}}_0$ = initial position and velocity vectors, respectively,

t = duration of extrapolation, and

μ = Earth gravitational parameter.

The constant gravity approach requires significantly less code than the Kepler approach but produces greater errors in extrapolation over long durations. The actual Kepler-based equations are much more complicated than Eq. 13 and require almost 50 times more processing time than the constant gravity approach.

Figure 4a shows position error results from extrapolations using the constant gravity approach on a generic 1500-km-range TBM. The calculated error is the distance between the coasted position and the ground truth position of the ballistic object. Based on the accuracies of the presently modeled radars, this approach is appropriate for short durations of coast. Figure 4b shows the performance of the Kepler approach on the same target. Because its performance is so much better than the constant gravity approach, a different color scale is used. The Kepler approach is clearly more appropriate for extrapolations over longer durations. Consequently, to reduce simulation execution times, ACES uses the constant gravity approach for coasting over short durations, such as between link updates, and the Kepler approach for coasting over long durations, such as predicting impact ellipses and engageability.

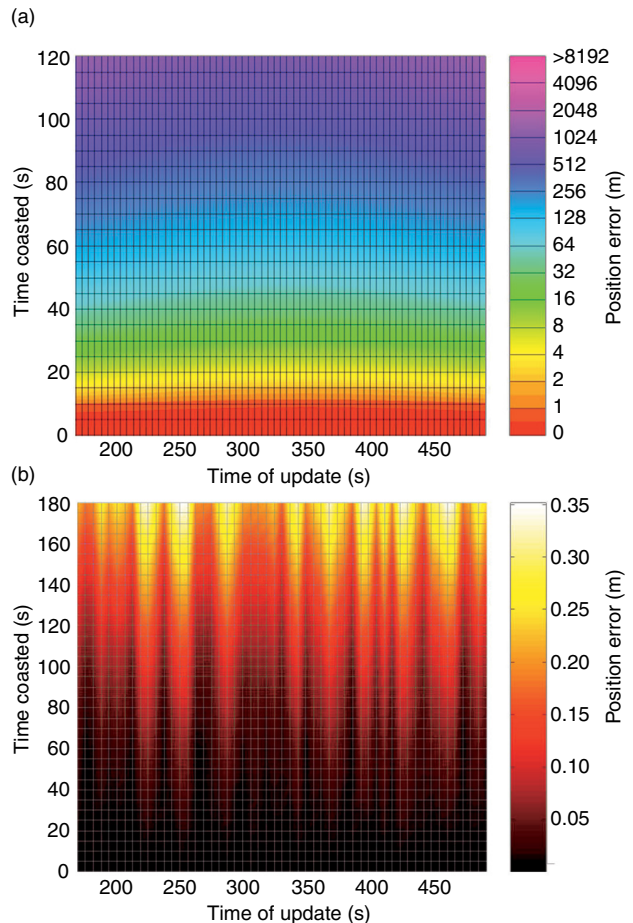


Figure 4. Extrapolation error for the (a) constant gravity approach and (b) Kepler approach.

CORRELATION OF LOCAL AND NETWORK TRACKS

Each unit in the simulation creates and maintains a unique set of local tracks. Units also exchange track information in accordance with the capabilities and constraints of modeled networks. Currently, ACES simulates two types of networks: (1) the Time Division Multiple Access Data Link (TDL), which is based on Link 16, and (2) the Sensor-Based Network (SBN), which is based generally on the performance of the Cooperative Engagement Capability (CEC). A more detailed description of ACES network modeling can be found in the article by McDonald et al., this issue.

Remote tracks are received via the TDL network. The track originates from a single unit, the one with the highest-quality track for that object. The remote track has the same random error as the local track on the sending unit but a different bias error. The bias error is different because the units perform a relative navigation process to eliminate unit-to-unit biases. Bias errors for each unit, representing the residual relative navigation bias, are selected by random draw at the beginning of the simulation and held constant throughout the scenario.

Composite tracks are produced from data received via the SBN network. The receiving unit combines data from all units contributing to a given composite track. In ACES this combination is a weighted average, which provides a better estimate of the track state than any single unit's data. The composite track has a smaller random error because more data are used to form the estimate. Bias errors are added to the composite track state to represent the residual bias errors remaining after the gridlocking process. These bias errors are selected by random draw at the beginning of the simulation and are held constant throughout the scenario.

The remote and composite tracks from the TDL and SBN, respectively, are correlated to the locally held tracks on each unit. This correlation process attempts to determine whether two tracks are actually representations of the same object. The same basic method is currently used for both the TDL and SBN.

Within ACES, the timing of the correlation process differs between the TDL and SBN. Correlation with TDL tracks is performed when a unit has locally held tracks from its sensors and it receives remote track reports from the data link. The TDL tracks received and local POTs are the only ones considered for correlation. A track must pass several other tests to become a candidate for correlation calculations. The track accuracies must be greater than a given threshold, and the track must not be in boost phase. Only local tracks that are not correlated are considered candidates. All local and remote tracks that meet these requirements are eligible for correlation. The SBN performs correlation between

local and composite tracks periodically as part of the process of updating composite tracks. With the SBN, correlation also occurs periodically among the composite tracks to eliminate dual tracks.

Once two tracks are selected to undergo the correlation calculations, a common time is found at which to do the calculations. In ACES, this is the latest of the last update times for the tracks. The state vectors of the tracks are extrapolated to this time using the constant gravity approach discussed previously. The position covariance matrices are also extrapolated, but the velocity matrices are not.

With the two tracks now at the same time, statistical comparisons can be made to determine whether the tracks represent the same object. The Mahalanobis distance and velocity values are calculated using the state vectors from the two tracks and their respective covariance matrices. These calculations normalize the separation by the error and express it as a nondimensional scalar quantity. The Mahalanobis distance value is

$$\text{MDV} = (\bar{\mathbf{x}}_R - \bar{\mathbf{x}}_L)^T (P_{pR} - P_{pL})^{-1} (\bar{\mathbf{x}}_R - \bar{\mathbf{x}}_L), \quad (16)$$

where $\bar{\mathbf{x}}_R$ is the remote track position vector, $\bar{\mathbf{x}}_L$ is the local track position vector, and P_{pR} and P_{pL} are the remote and local position covariance matrices, respectively. The Mahalanobis velocity value calculation is done analogously to the Mahalanobis distance value calculation.

The sum of the Mahalanobis distance and velocity values produces a statistic that follows a chi-squared distribution with six degrees of freedom. If the statistic is less than a designated confidence threshold, it is concluded that the two tracks could correlate.

Because a TDL track may correlate with only one other track, a method is needed to select among tracks meeting the confidence threshold. In ACES, this method chooses the remote track with the smallest local-remote Mahalanobis sum.

FUTURE DIRECTIONS

The level of radar modeling in ACES was selected to ensure the presence of the most common radar track phenomena and to maintain a flexible structure to incorporate other functionality. Methods of approximating some effects are pursued in the interest of reducing processing time to support Monte Carlo analyses while still ensuring that the effects create a degree of reality appropriate to what is being studied.

Based on the needs of the analysts, the fidelity of certain radar aspects may need to be increased or new capabilities may need to be added. Perhaps actual track filtering algorithms will be desired or the capability to model environmental conditions other than standard

atmosphere. The complexity of the radar modeling will also increase as ACES evolves to support other missions. Functionality will be added, and current methods may be modified to support these new areas.

When ACES begins support in AAW, sea and land clutter will be incorporated, as will moving target indicator processing. Support for OCMD will require the

modeling of airborne radars, and digital terrain elevation data will be used to determine radar blockages and clutter. Infrared sensors may also need to be included.

The engineers involved in maintaining the ACES sensor model must continue to envision possible future capabilities in order to maintain a flexible structure that can adapt to modeling needs as they arise.

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