Electromagentic Diversity and EMI Implications for Multiple Co-sited Radars and Targeting Applications

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Abstract—Real-time fusion of data collected from a variety of co-located radars that acquire information in a cooperative manner from multiple perspectives and/or different frequencies, is being shown to provide a more accurate and effective way of tracking complex targets in a multi-target scenario. This is more advantageous than employing a single radar or a group of radars operating independently. This paper describes a cooperative multi-sensor approach in which multiple radars operate together in a non-interference limited manner. A three-fold approach is presented: (i) applying multiobjective joint optimization algorithms to set limits on the operational parameters of the radars to preclude electromagnetic interference; (ii) measuring and processing radar returns in a shared manner for target feature extraction based on electromagnetic diversity principles in conjunction with target scattering cross sections; and (iii) employing feature-aided track/fusion algorithms to detect, discriminate, and follow real targets from clutter noise. The results of computer simulations are provided that demonstrate the advantages of this approach.

Keywords—Electromagnetic Interference/Compatibility; System of Systems; Sensor Fusion; Radar Cross Section; Sensor Integration; Multi-Sensor Feature-Aided Extraction

I. Introduction

Electromagnetic diversity can be achieved in a variety of ways. For the present application, we first emphasize the use of frequency and spatial diversity schemes for the multi-sensor, multi-target environment. This is done in an effort to optimize targeting objectives while simultaneously minimizing electromagnetic interference i.e., "collisions" that might arise when deploying a cooperative multi-radar network and the intercommunications and coordinations that must take place.

The exploitation of frequency and spatial diversity in a cooperative multi-radar scenario is intended to enhance our current abilities to detect and track multiple moving targets in a highly dynamic battlespace. The challenge is one of accurately detecting and tracking true targets in real time and in the presence of clutter. The clutter in this case is attributed to the *adversary noise cloud* which is intended to mask the real targets from radar detection and thus defeat the radars at their own game. The multi-target discrimination and tracking problem is further exacerbated by requirements for minimizing interferences among the cooperative radar elements. Because target scenario states are constantly changing and the radars must adapt as necessary, it is important to ensure that the collection of radar sensors do not interfere with each other based on signal-to-interference plus noise ratio (SINR); otherwise, efficient real-time data throughput within and between sensor platforms can be compromised resulting in the loss of target tracking ability. Real-time performance is also predicated on having sufficient signal/data processing speed and capacity at the sensor side, as well as ensuring that the sensors are properly calibrated.

Furthermore, the goal of data fusion is to operate on a combination of radar sensor measurements, features, track states, and object type and identification likelihoods to produce a single integrated picture of the air space to a high degree of accuracy. Technologies that enable this synergistic fusion and interpretation of data at several levels from disparate, distributed radars and other sensors should enhance system acquisition, tracking and discrimination of threat objects in a cluttered environment and provide enhanced battle space awareness. Again, limiting the effects of environmental electromagnetic interference (EMI) on the collection of radars in relatively close proximity is paramount.

To reiterate, the emphasis here is on exploiting frequency and spatial diversity. This is accomplished using multiple next generation (XG) aperture radar systems for target feature extraction and to provide useful information to tracking/estimation algorithms for multi-target tracking tasks and to assist in discriminating true targets from noise objects. The general scenario is illustrated in Figure 1. Such radars employ adaptive waveform techniques that provide the basis for the frequency diversity in order to evoke a certain desired response based on the target characteristics, and maximize the probability of real

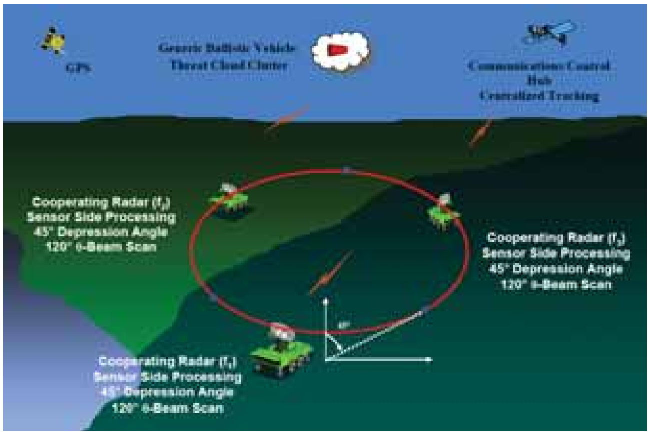

Figure 1. Ground-Based Multi-Radar Target Detection/Tracking.

time target detection/tracking. Spread spectrum waveforms and frequency agility are used to provide the added advantage of low probability of intercept (LPI) and anti-jam (A/J) capabilities. However, the electromagnetic environment produced by the radars themselves can generally lead to catastrophic interference and an overall reduction in multi-radar performance unless the adaptive functions of the radars can be properly managed. One technique to preclude interference-limited operation of this type is through the application of *Transmission Hyperspace* schemes [1]. Once the potential for EMI is minimized, cooperative radar scattering returns can be used in the feature-aided tracking and detection algorithms to achieve the desired objectives of the multi-target tracking/discrimination problem.

II. Multi-Sensor Interference Management

Essentially, the radars will produce time-variant electromagnetic signals as they adapt waveforms to "match" dynamically changing target conditions. Consequently, a redistribution of the power spectral densities occurs in accordance with changes in operational modes of the radars and variations in waveform parameters to enhance target detection and tracking performance. However, time-variant and randomly changing power spectral densities can lead to potential interference conditions for the system of cooperating radar sensors. Several techniques have been researched in recent years to alleviate the potential EMI problem at this level by employing multi-sensor interference management. For instance, one approach is to enable the sensors with a *Transmission Hyperspace* (*TH*) broker. Here, multiobjective joint optimization schemes (alternatively, *game theory* based approaches can be equally applied) are used to optimally assign frequency, time, code/modulation, location, etc. in order to satisfy a specific multiobjective function (e.g., target detection), including minimizing EMI for the system of sensors. Although the concept of *TH-enabled cells* has been discussed in the literature [1], we briefly recap some of the salient features of the approach below, as it applies to interference management.

A. Multiobjective Joint Optimization

The *TH* approach enables the effective and efficient joint utilization of all orthogonal electromagnetic (EM) transmission resources, including, but not limited to, time, frequency, geographic space, modulation/code, and polarization. This multidimensional environment is intended to convey the notion of an n-dimensional resource space in which each dimension allows orthogonality amongst users. Currently, there are no known technological approaches to RF transmission in spectrum management that consider all of these dimensions jointly, and certainly none that consider them in the context of a system optimization problem. One of the benefits of employing this approach is the ability to effectively manage the spectrum for a distributed multi-sensor system in order to reduce or essentially eliminate the potential for EMI.

There are a number of possible approaches to achieving multiobjective joint optimization for the present problem. Statistical optimization is one approach. Linear and nonlinear optimization, meta-heuristics, constraint satisfaction, and multidisciplinary optimization are yet others. Evolutionary algorithms offer a very promising approach assuming the computational bottlenecks can be overcome to support real time requirements. However, the details of these various approaches are left to the literature [1]. Suffice it to say that many promising methods exist to attack the spectrum management and interference reduction problem.

B. Relevant EMI/C Factors

There are increasing demands for improved performance of future communication and radar systems that will be co-located. One approach to optimizing performance is through the design of novel diverse waveforms. Recent advances in hardware technology make it possible to design waveforms in real time that maximize SINRs, improve resolution, and increase information transfer. Temporal and spatial waveform diversity can support the following concepts: reliable communications in realistic multipath environments, radar with multiple mission (tracking and imaging capability), interferometric radar and communications for better resolution and throughput, multistatic radar for improved discrimination, and integrated radar/communications in severe interference environments.

The successful implementation of the multiobjective joint optimization implies electromagnetic compatibility (EMC) between its many users. A user is said to be electromagnetically compatible provided it satisfies three criteria: (1) it does not cause interference with other users, (2) it is not susceptible to emissions from other users, and (3) it does not cause interference with itself. Central to the goal of EMC is the concept of orthogonality between the users as determined by how *TH* cells are assigned in the multi-dimensional RF resource space.

However, perfect orthogonality between users is unlikely to be achieved in typical real world applications. For example, in the spatial dimension it is possible to design the main beams of transmit and receive antennas such that they do not overlap in specified directions. However, all antenna patterns include sidelobes which do overlap. Analogous statements apply to frequency domain spectra. These overlaps can lead to severe interference when a high power emitter, such as a radar, is collocated near a highly sensitive digital receiver, such as a wireless device. In the polarization domain, orthogonality between users can be compromised by multiple reflections. As another example, the nonlinearities present in all electronic systems can generate unintended consequences for users of the RF Resource Space. Thus, a frequency hopping spread spectrum system produces a complicated pattern of harmonics, intermodulation products, and spurious responses that may cause problems for users in both nearby and distant frequency-domain cells of the RF Resource Space. In addition, the various domains of the resource space are all interrelated, as predicted by Maxwell's equations and Fourier analysis. Therefore, orthogonality in one domain can lead to undesired results in another. For example, shorter duration times for pulses in a time-division multiple access scheme causes wider frequency spectra that could be troublesome to some of the users.

In the present context, perfect orthogonality between users is referred to as <u>strict</u> orthogonality. Orthogonality that is intended, but not strictly achieved, is referred to as <u>loose</u> orthogonality. EMC applies automatically to those users for which strict orthogonality exists. On the other hand, EMC may or may not apply to those users for which there is loose orthogonality. Loose orthogonality is not necessarily to be avoided. In the following paragraphs, we briefly review this approach where loose orthogonality is employed in order to increase the number of users in a CDMA direct sequence spread spectrum (DSSS) system. This will be the fundamental basis for the scheme applied to the multi-radar, multi-target tracking/discrimination problem.

C. CDMA DSSS System Illustration

Consider a CDMA DSSS system for which all users have the same chip rate, R_c, data rate, R_b, and carrier frequency, f_o, but are assigned different spreading codes which are nearly orthogonal. The chip rate is chosen such that the power spectral density (psd) of each user fills the common frequency band centered at f_o having bandwidth, B_o. This scheme is illustrated in Figure 2(a) where all users have identical power spectral densities and a maximum processing gain given by $L_o = B_o/B_b$ where B_b is the data signal bandwidth. Because the codes are nearly orthogonal, a residual component due to each undesired signal exists at the correlator output of each receiver and limits the total number of users in the band to K_o such that a prespecified probability of error, P_e, is achieved. Because each DSSS signal has the maximum possible processing gain, it might be conjectured that the number of DCMA DSSS users for the given frequency band and probability of error cannot exceed K_o.

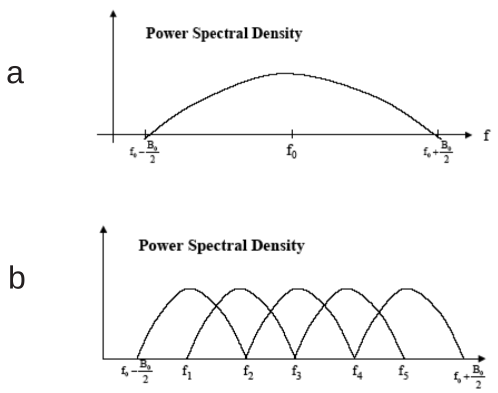

Figure 2. PSD of (a) each CDMA DSSS system and (b) sub-division of original frequency band.

However, consider the scheme illustrated in Figure 2(b) where the original frequency band has been subdivided into 5 sub-bands. The center frequency bandwidth B_o has been subdivided into 5 sub-bands, where each sub-band is given by

$$\begin{array}{lll} f_1 = f_o - B_o/3, & f_3 = f_o & f_5 = f_o + B_o/3 \\ f_2 = f_0 - B_o/6, & f_4 = f_o + B_o/6 & \end{array} \quad (1)$$

Let $K_k, k = 1, 2, \ldots, 5$, denote the number of CDMA DSSS users in each sub-band where K_k is maximized such that the probability of error for each user does not exceed that of the scheme in Figure 2(a). It has been shown both by analysis and computer simulation that the total number of users for the scheme of Figure 2(b), given by

$$K = K_1 + K_2 + K_3 + K_4 + K_5 \quad (2)$$

is approximately 20 percent larger than K_o. This result is partly explained by the loose orthogonality that exist between the overlapping sub-bands of Figure 2(b) (Note that the peak of one sub-band is placed at the null of the neighboring sub-band). Also, the loose orthogonality of the spreading codes allows for more different codes of a fixed length to be generated that would be possible if strict orthogonality was enforced.

Nonetheless, loose orthogonality may result in electromagnetic interference (EMI) which reduces the quality of service (QoS) required by one or more users of the RF resource space. Consequently, it is proposed that the approaches to be identified in this research for joint optimization of the multiple orthogonalizing transmission parameters be constrained by EMC considerations. Assignments that are likely to cause unacceptable losses in QoS will be removed from consideration.

For this purpose, users of the RF resource space having potential for undesired signal coupling will be identified. These will be divided into sets of emitter and receptor ports having specified coupling paths. It will be assumed that one or more emitters can couple to a given receptor while a given emitter can couple to one or more receptors. Using the resource space dimensions, multidimensional profiles are established for each emitter and receptor port. These are used, along with characterizations of the coupling paths, to determine whether or not the power from unintentional users at each receptor port exceeds the susceptibility threshold for that port. Because of the complexity of the above approach, simple *rules of thumb* can be used to demonstrate the EMC constrained joint optimization procedure. These can then be refined so as to yield more accurate predictions.

These EMC considerations should be embedded into the development of the system so that users who are assigned particular coordinates are not prevented from operating at acceptable levels of performance.

III. Measuring Scattering Cross Sections

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IV. Measured Scattering Cross Sections

Next, we return to the basic problem of target object discrimination and tracking as illustrated in Figure 1. Three ground radars are shown. In this example illustration, each is assigned to operate at a different frequency, and has a 120 deg. scan angle sweep and an elevation/depression look angle of 45 deg. with respect to the ground and target region. The multi-radar target detection/tracking system will include the following functions: target detection, measurement acquisition, feature extraction, target tracking, discrimination and classification. These functions are mutually dependent, and the performance of one function will affect or be related to another. Therefore, these function entities should be considered and designed jointly to achieve a better system level performance.

One of the major functions of these radars is to measure the target scattering cross sections and provide information to a central communications hub for processing of the raw returns. The advantage of having frequency and spatial diversity is somewhat intuitive in that these cooperative radar elements working together in a "network" can provide much information about the physical characteristics of the target object(s).

Next, consider techniques for combining the measurements of radar returns or measured target cross sections. This is done in order to perform feature extraction and provide amplitude information to the support the estimation and tracking stages of the radar signal processing chain. Here we assume that the radars are high resolution range (HRR) radars [2], which are spatially distributed and where again, each operates at a different frequency. The HRR return data is used as part of a feature extraction process. Features (amplitudes) are then provided to an estimator/tracker and then to a discriminator/classifier.

Figure 3 shows a representative composite "snapshot" of the multi-target scattering returns using the multiple radar system. The peaks observed in Figure 3 generally correspond to specific features of the measured targets for vertically (VV) polarized radar returns, which were "measured" at different aspect angles and frequencies. Depending on the occurrences and phase information related to the measured target returns, one can discern the true targets from the noise objects. In particular, the various frequencies of the multiple radars will evoke a different set of responses (e.g., resonant peaks) from the target objects as a function of their electrical size at the frequencies of interest. The radars may then adapt their waveforms to further interrogate targets in order to optimize multi-target recognition, tracking, and discrimination in real time. This stochastic-based process is used to further evoke and measure target returns over time in an effort to accurately discriminate and keep track of the multiple targets in the battlespace. The importance of limiting interference noise in the process of performing these functions is key and is based on the interference management scheme discussed above.

Recall in the example shown in Figure 3 that there may be multiple targets present including noise objects. The simulations performed focused a small number and limited class of

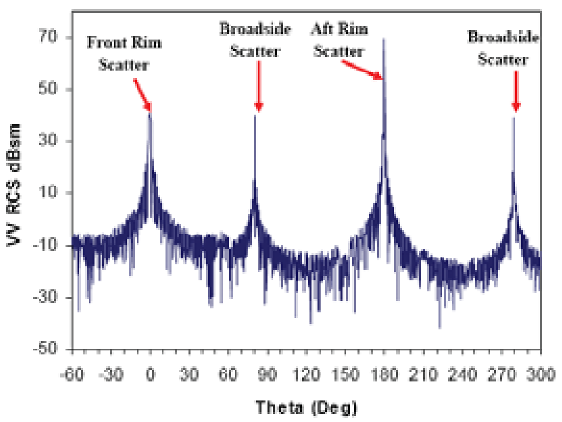

Figure 3. Composite of Vertically Polarized Multiple Radar Returns for Multi-Target Tracking/Discrimination.

canonical target objects such as perfectly electrically conducting (PEC) cones and frusta, which exhibit multiple segments, surface areas and rim-edges. The objects simulated were also of varying physical size and dimensions. As expected, the highest amplitude returns for the various-sized objects in the simulations correspond predominantly to the broadside and rim-edge scatter from these objects. It is up to the discriminator to determine which returns (amplitudes) correspond to real targets versus decoys based on a predefined set of signature criteria.

Next, these amplitudes are extracted as part of the feature extraction process and this information is then fed to the estimator/tracking block of the multi-radar processing chain.

V. Feature-Aided Tracking and Discrimination Using Radar Cross Sections

The task of traditional radar target tracking is to establish target kinematic trajectories from sequences of noisy kinematic measurements in the presence of false alarms and countermeasures [3], [4]. However, difficulty arises in traditional target tracking when target density becomes high and targets move together, and when ambient electromagnetic noise and clutter arise which could result in merged tracks and switched track identities. Again, the importance of reducing interferences at all levels is underscored here!

Once the tracks are initiated, the multiple targets should be tracked accurately. One of very important issues in multi-target tracking is the data association problem. The association step compares measurements, and attempts to collect measurements originating from the common real world object into a single track. The difficulty is in distinguishing from which target, if any, each measurement originates. This is addressed by measurement-to-track association techniques.

With the advance in sensor devices such as HRR radar and synthetic aperture radar (SAR), additional information regarding target identification becomes available, which could be very valuable in helping data association using feature (electromagnetic signature) data. These data are extracted from HRR radars and fed to the tracker to enhance data association capability, and hence the tracking performance, especially for stressing and complicated scenarios.

On the other hand, the output of the trackers, such as velocity and acceleration of the targets, can be very helpful for the identification and classification of the targets. In [5], the authors have applied both Bayesian and Dempster-Shafer methods to develop target identification algorithms, using features including target speed and acceleration estimated by a tracker.

As a result, by limiting the adverse effects of EMI at the start of the radar signal processing chain, to allowing information transmitted from feature extractor to tracker, and from tracker to classifier, the system performances, including both for target tracking and target classification, should be improved significantly.

A. Multi-Target Tracking

There are many algorithms to solve the problem of multi-target tracking in the presence of clutter and ambient noise. There has been some research indicating that considerably improved performance is achievable when some amplitude information (AI) is delivered to the tracker along with the location measurements [9], [10]. Target tracking with the assistance of feature or feature-aided tracking (FAT) is a relatively new research area [11]–[14]. The feature (or its wavelet transform) obtained by HRR radar has been shown to be very effective to improve the data association performance.

Since data association performance and tracking robustness against misdetections, decoy and debris can be improved through the FAT methods, HRR profile or other feature information is incorporated, such as signal amplitude or target ID to the tracker. The benefits of the additional feature information can then be assessed. Note that the track initiation process can also be aided by extra features other than amplitude, to achieve a higher probability of track detection and a more accurate track estimate.

B. Target Discrimination Based on Interference Reduction and Scattering Cross Sections

Target discrimination is essential for any type of weapon or ballistic missile defense system. For example, decoys may have radar cross-section (RCS) levels similar to those of the warhead, which makes robust target identification based solely on RCS levels difficult.

Narrowband radars usually lack sufficient range resolution to allow a direct measurement of target length, although they are generally useful for tracking and coarse motion estimation. Unlike narrowband radars, wideband radars allow a much larger suite of target discrimination algorithms to be employed for real-time range Doppler imaging and phase-derived range estimation.

In [15], coherent fusion of electromagnetic signature data from multiple sensors operating over different frequency bands is discussed within the context of an EM interference suppressed environment. In [16]–[19], target recognition/identification based on HRR radar signatures has been studied. In [20], a wavelet de-noising scheme is used to aid the automatic target recognition based on HRR signatures. The authors show that a large portion of HRR signature content is non-discriminatory. The wavelet de-noising process removes the non-discriminatory information, and leads to a remarkable improvement in classification accuracy.

In addition to the features extracted from the HRR data, we have the target state estimates, as outputs from the tracker. They provide the dynamic motion information regarding the multiple objects in the radar field of view, which are very helpful in target recognition and should be incorporated in the target classifier. This is due to the fact there exist differences not only in size and shape, but also in motion dynamics between the real targets and non-threatening objects (decoys, countermeasures, and debris).

To fuse different features, including target state estimates and HRR signatures, a target identifier is needed. Either a Bayesian or a Dempster-Shafer combiner can be used to accomplish this.

VI. Example: Amplitude Feature-Aided Tracking at Reduced Electromagnetic Inteference Levels

To illustrate the advantage of feature-aided tracking in the absence of interference, a ballistic vehicle tracking example is assumed, where the amplitude information is transmitted to the tracker as well as the position information. In the discussions which follow, emphasis is placed on the parameters used to characterize amplitude and how clean amplitude information is needed in certain target tracking algorithms. The details of the step-by-step derivation of the target dynamic model and corresponding measurement models as well as the calculation of covariance and false alarm rate are omitted in the present discussion.

A. Signal Amplitude Model

We denote by a the amplitude (magnitude-square output of a matched filter) of a radar return signal. The pdf of a when the signal is due to noise only is denoted by $f_0(a)$ and the corresponding pdf when the signal originated from the target is $f_1(a)$. Assuming a Swerling I target fluctuation model, we have

$$f_0(a) = \exp(-a), \quad a \geq 0 \tag{3}$$

$$f_1(a) = \frac{1}{1+\rho} \exp\left(-\frac{a}{1+\rho}\right), \quad a \geq 0 \tag{4}$$

where ρ is the average SNR.

A suitable threshold, denoted by τ is used to declare a detection. As a result, the probabilities of detection and false alarm are

$$P_D = \int_\tau^\infty f_1(a)\, da = \exp\left(-\frac{\tau}{1+\rho}\right) \tag{5}$$

$$P_{FA} = \int_\tau^\infty f_0(a)\, da = \exp(-\tau) \tag{6}$$

The density functions corresponding to the output of the threshold detector are truncated versions of the previous pdfs.

$$f_0^\tau(a) = \frac{1}{P_{FA}} f_0(a) = \exp[-(a-\tau)], \quad a \geq \tau \tag{7}$$

$$f_1^\tau(R) = \frac{1}{P_D} f_1(R) = \frac{1}{1+\rho} \exp\left[-\frac{(a-\tau)}{1+\rho}\right], \quad a \geq \tau \tag{8}$$

Finally, we define the amplitude likelihood ratio l, which is used in the derivation of the amplitude feature aided tracker, as

$$l(a) = \frac{f_1^\tau(a)}{f_0^\tau(a)} = \frac{1}{1+\rho} \exp\left[\frac{\rho}{1+\rho}(a-\tau)\right] \tag{9}$$

B. PDAF and PDAF-AI

First, we assume there is only one target for simplicity. We also assume that at each scan, among the measurements of a radar, at most one of them originates from the target, whereas the others are just false alarms. To track the target in the presence of clutter and other noise (false alarms), we adopt a probabilistic data association filter (PDAF).

If amplitude information (AI) is available, a modified version of the PDAF, i.e., the PDAF-AI has been developed to take advantage of the extra feature, where amplitude information functions as a discriminating feature, and the improvement relative to the original PDAF can be dramatic. Interested readers can find a detailed description about the PDAF and PDAF-AI in [6].

The procedure is then extended to two or more sensors which at first are collocated and then spatially separated. Then, frequency diversity as a function of the AI is introduced to demonstrate the improvements in overall discrimination and tracking performance.

Table 1. In-track percentage for various situations.

ρ (dB)	$\lambda (m^{-2})$	PDAF 1-Sensor	PDAF-AI 1-Sensor	PDAF 2-Sensor	PDAF-AI 2-Sensor
5	5×10^{-6}	0	53	9	90
5	5×10^{-7}	34	70	74	93
10	5×10^{-6}	0	88	19	95
10	5×10^{-7}	86	99	91	99

Table 2. RMSE for various situations.

ρ (dB)	$\lambda (m^{-2})$	PDAF 1-Sensor	PDAF-AI 1-Sensor	PDAF 2-Sensor	PDAF-AI 2-Sensor
5	5×10^{-6}	—	109.0	74.0	77.4
5	5×10^{-7}	143.0	138.9	95.3	117.5
10	5×10^{-6}	—	79.8	70.8	46.2
10	5×10^{-7}	88.5	69.6	85.3	46.5

VII. Simulation Results

Simulation results were obtained using 100 Monte Carlo runs with the following scenario: the ballistic vehicle enters the sensor surveillance region at $t_0 = 0s$ with initial position $\xi_0 = \eta_0 = 10^5 m$ and initial velocity $\dot{\xi}_0 = \dot{\eta}_0 = 1500\, m/s$. $\sigma_v = 0.5\ m/s^2$, $\sigma_m = 100\ m$, $T = 0.5s$.

An example is shown in Figure 4. As can be seen, the PDAF loses the track of the target very quickly, while the PDAF-AI holds the track for the full 50 scans, due to the extra amplitude information.

Next, we compare the performance of the PDAF and PDAF-AI under various system parameters. Here, we not only investigate the single-sensor case, but a two-sensor case, to have a better understanding on how the tracking performance improves as more resources are available to the fusion center.

In the two-sensor case, the performances of the two sensors are assumed identical, and measurements at the two sensors are assumed independent of each other. Data are fused in a centralized manner, meaning that raw measurements are transmitted to the fusion center for target tracking. The PDAF or PDAF-AI filter sequentially updates its state estimate with data from the two sensors [6].

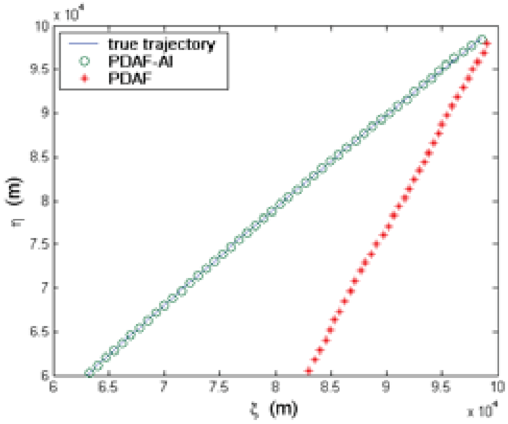

Figure 4. Example of Track with $\rho = 10\, dB$, Clutter Density $\lambda = 5 \times 10^{-6}\, m^{-2}$, Number of Sensors: 1.

The in-track percentage for various system parameters is shown in Table 1. A simulation is judged as in-track if at the 100th scan, the total number of validated measurements in the validation gate [6] is less than or equal to 10, and the true and estimated positions are less than $10\sqrt{2}\sigma_m$ apart. From this table, it is clear that the PDAF-AI has a significant improvement over the PDAF, especially when the clutter density is high ($\lambda = 5 \times 10^{-6}\, m^{-2}$).

In Table 2, tracking performance in terms of root mean square error (RMSE) is listed. Note that only results from the “in-track” simulation runs are included to calculate the RMSE. We can see that in most situations, the PDAF-AI has a lower RMSE error than the PDAF.

A. Conclusions

From both tables, we observe that the PDAF-AI has a very robust performance, even when the SNR is as low as 5 dB and the clutter density is very high. Another important conclusion is that by utilizing data from multiple sensors, the performances of the tracker, both in terms of in-track percentage and RMSE, are improved significantly especially under EMI-free conditions.

This example shows that, even with the help of very simple signal amplitude features and reduced EMI plus external noise/clutter, the system can achieve a much better performance for data association and target tracking.

However, more simulations are required using additional sensors and associated feature information. This will help to further confirm trends and determine the critical number of sensors that would be needed and to more fully quantify anticipated gains in performance. An effort to accomplish this is currently underway, which will also investigate levels for acceptable interference under non-ideal conditions.

VIII. Summary

This paper discussed the results of investigations aimed at applying a cooperative multi-sensor approach to enhance the acquisition, tracking, and discrimination of moving targets with reduced electromagnetic interference and low false alarm rate. Multiple radars were assumed to operate together in a non-interference limited manner. A three-fold approach was discussed: (1) applying multiobjective joint optimization algorithms to set limits on the operational parameters of the radars to preclude EMI based on the *Transmission Hyperspace* paradigm; (2) measuring and processing radar returns in a shared manner for target feature extraction based on waveform diversity techniques; and (3) employing feature-aided track/fusion algorithms to detect, discriminate, and track real targets from the adversary noise cloud.

Computer simulations showed that with the help of simple signal amplitude features obtained from scattering cross section measurements using spatially and frequency diverse radars, the overall sensor system can achieve a much better performance for data association and target tracking.

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