Real-Time Radar Data Fusion and Registration Systems for Single Integrated Air Picture

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ABSTRACT

Real-time fusion of data collected from a variety of radars that acquire information from multiple perspectives and/or different frequencies, is being shown to provide a more accurate picture of the adversary threat cloud than any single radar or 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, and where decision algorithms are applied to optimize the acquisition, tracking, and discrimination of moving targets with low false alarm rate. The approach is two-fold: (i) measure and process radar returns in a shared manner for target feature extraction by exploiting frequency and spatial diversity; and (ii) employ feature-aided track/fusion algorithms to detect, discriminate, and track real targets from the adversary noise cloud. The results of computer simulations are provided that demonstrate the advantages of this approach.

Keywords: Multisensor fusion, radar cross section, sensor integration, feature-aided tracking, automated target recognition

1. INTRODUCTION

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 meant 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 independent radar sensors do not interfere with each other; 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 air 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.

The use of next generation (XG) distributed aperture radars and ultra-wideband (UWB) technologies for target feature exploitation is central to this approach. The emphasis here is on exploiting frequency and spatial diversity using multiple radar systems to support feature extraction and provide useful information to tracking/estimation algorithms for multi-target tracking tasks and to assist in discriminating true targets from noise objects. Such radars employ adaptive waveform techniques in order to evoke a certain desired response based on the target characteristics, and maximize the

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probability of target detection and the accuracy of target tracking in real time. Assuming interferences can be effectively minimized, cooperative radar scattering returns can be used in the feature-aided tracking and detection algorithms.

2. MEASURED SCATTERING CROSS SECTIONS

The basic problem of target object discrimination and tracking is first addressed within the overall context of measuring scattering cross sections. To begin, the multi-radar target detection/tracking/classification 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.

Now 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 support the estimation and tracking stages of the radar signal processing chain. Here we assume that the radars are high range resolution (HRR) radars [1], which are spatially distributed and where each operates at a different frequency. An illustration of a ground-based configuration which was used in computer simulations to analyze the present problem is shown in Fig. 1. The HRR return data is used as part of a feature extraction process. Features (amplitudes) are then provided to an estimator/tracker and discriminator/classifier.

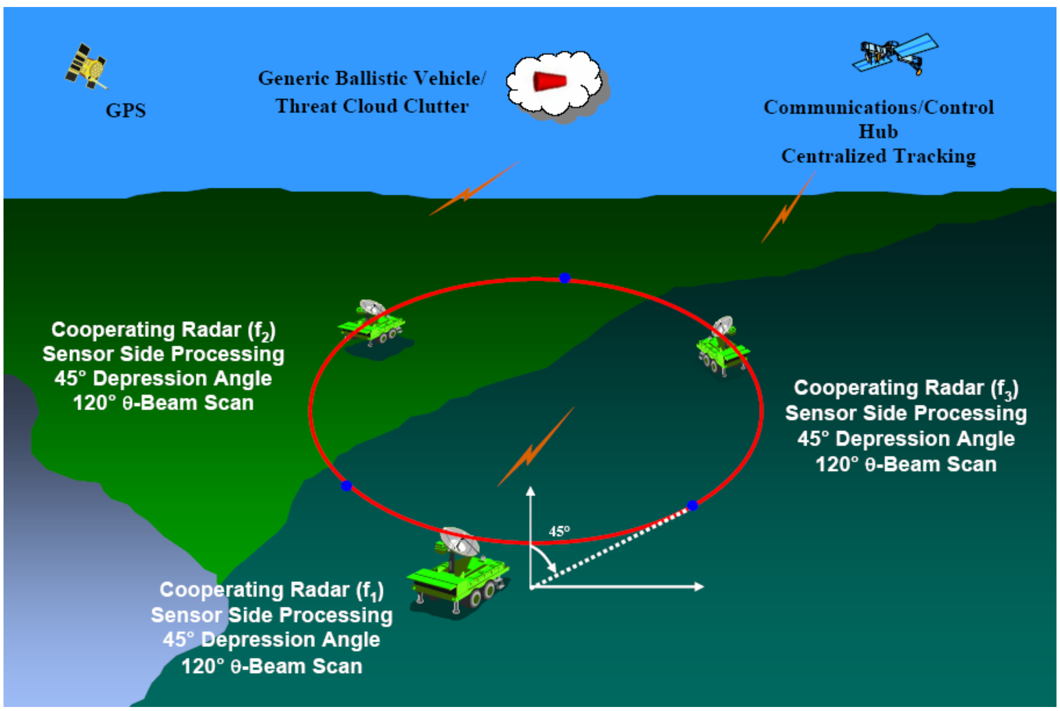

Figure 1: Ground-based multi-radar detection/tracking.

Fig. 2 shows a representative composite "snapshot" of the multi-target scattering returns using the multiple radar system. The peaks observed in Fig. 2 correspond to specific features of the measured targets for vertically (VV) polarized 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 procedure 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.

Recall in the example shown in Fig. 2 that there may be multiple targets present including noise objects. The simulations were performed for a small number and limited class of 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.

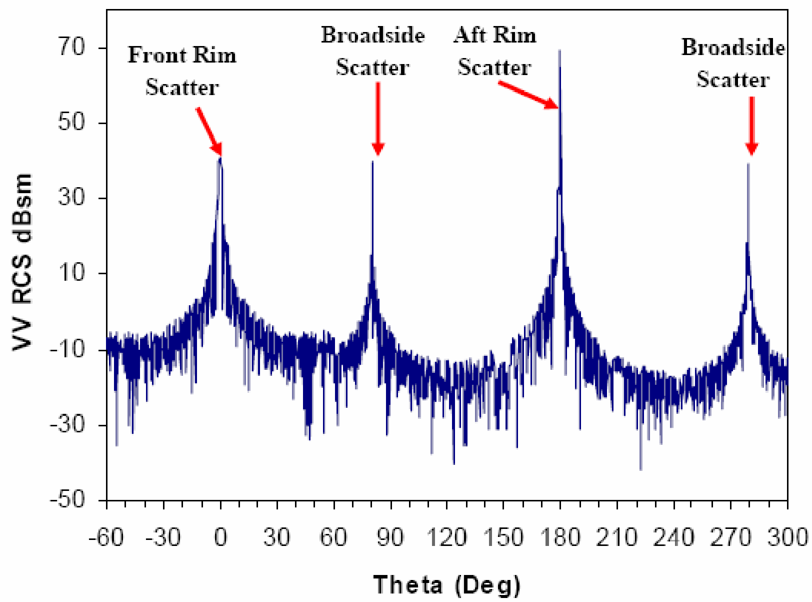

Figure 2: Composite of vertically polarized multiple radar returns for multi-target tracking/discrimination.

Next, the approach would be to extract these amplitudes as part of the feature extraction process and feed this information to the estimator/tracking block of the multi-radar processing chain. In the discussions which follow and in the example described below, actual amplitude information was not explicitly used; rather, its use is implied. Efforts are in process by the authors to attempt to more directly couple the amplitude information to the estimator/tracking block and associated algorithm suite. The results of this work will be reported in a future publication.

3. FEATURE-AIDED TRACKING AND DISCRIMINATION

The task of traditional target tracking is to establish target kinematic trajectories from sequences of noisy kinematic measurements in the presence of false alarms and countermeasures [2, 3]. However, difficulty arises in traditional target tracking when target density becomes high and targets move together, which could result in merged tracks and switched track identities.

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 (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 [4], 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 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.

3.1 Multi-target tracking

There are many algorithms to solve the problem of multi-target tracking in the presence of clutter, including the Multiple Hypothesis Tracker (MHT), S-D assignments, and the Joint Probabilistic Data Association filter (JPDAF) [5]. Because the JPDAF is a target-oriented approach, when the number of true targets is known a priori, it is appropriate to use the JPDAF. On the other hand, the MHT is a measurement-oriented method, in the sense that the probability that an established target or a new target gave rise to a certain measurement sequence is obtained. This feature allows inclusion of track initiation for new targets within the framework of the algorithm. However, an exhaustive MHT is impractical, because it requires the evaluation of an exponentially increasing number of feasible data association hypotheses. In practice, we adopt an alternative approach, the S-D assignment algorithms.

The multi-target/multisensor data association should work closely with other functions of the multi-sensor system, such as the target classification and identification. Usually tracking and classification are treated as separate problems, often using a separate suite of sensors or sensor modes and techniques to solve them. For example, tracking is usually performed using data from kinematic sensors (e.g., radar) while target classification is usually performed using data from identity or attribute sensors, such as electronic support measure (ESM) and HRRs. The joint tracking and classification problem has been investigated in [6, 7].

By using extra information from features obtained from sensors such as HRR, IR or EO sensors, the system’s data association and hence, tracking performances can be improved significantly. 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 [8, 9]. Target tracking with the assistance of feature or feature-aided tracking (FAT) is a relatively new research area [10-13]. 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.

3.2 Target classification/discrimination

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 [14], coherent fusion of signature data from multiple sensors operating over different frequency bands is discussed. In [15-18], target recognition/identification based on HRR radar signatures has been studied. In [19], 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.

4. EXAMPLE: AMPLITUDE FEATURE-AIDED TRACKING

To illustrate the advantage of feature-aided tracking, a ballistic vehicle tracking example was 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 amplitude information is used 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.

4.1 Signal amplitude model

We denote by a the amplitude (magnitude-square output of a matched filter) of a radar return signal. The probability density function (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

$$f_0(a) = \exp(-a), \quad a \geq 0 \tag{1}$$

and

$$f_1(a) = \frac{1}{1+\rho} \exp\left(-\frac{a}{1+\rho}\right), \quad a \geq 0 \tag{2}$$

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, respectively,

$$P_D = \int_\tau^\infty f_1(a)\, da = \exp\left(-\frac{\tau}{1+\rho}\right) \tag{3}$$

and

$$P_{FA} = \int_\tau^\infty f_0(a)\, da = \exp(-\tau)\,. \tag{4}$$

The respective density functions corresponding to the output of the threshold detector are truncated versions of the previous pdfs and are expressed as

$$f_0^{\tau}(a) = \frac{1}{P_{FA}} f_0(a) = \exp[-(a-\tau)], \quad a \geq \tau \tag{5}$$

and

$$f_1^{\tau}(R) = \frac{1}{P_D} f_1(R) = \frac{1}{1+\rho} \exp\left[-\frac{(a-\tau)}{1+\rho}\right], \quad a \geq \tau\,. \tag{6}$$

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

$$l(a)=\frac{f_1^{\tau}(a)}{f_0^{\tau}(a)}=\frac{1}{1+\rho}\exp\left[\frac{\rho}{1+\rho}(a-\tau)\right]. \tag{7}$$

4.2 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 (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 [5].

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.

5. PRELIMINARY SIMULATION RESULTS

Simulation results were obtained using 100 Monte Carlo runs with the following scenario: the ballistic vehicle enters the sensor surveillance region at $t_0 = 0$ s with initial position $\xi_0 = \eta_0 = 10^5 m$ (the two coordinates of the initial target position) and initial velocity $\dot{\xi}_0 = \dot{\eta}_0 = 1500\, m/s$ (the initial target velocity in two dimensions), $\sigma_v = 0.5\, m/s^2$ (the standard deviation of the process noise), $\sigma_m = 100\, m$ (the standard deviation of the measurement noise), and $T = 0.5\, s$ (the time interval between radar scans).

An example is shown in Fig. 3. 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, where λ is the spatial density of false alarms.

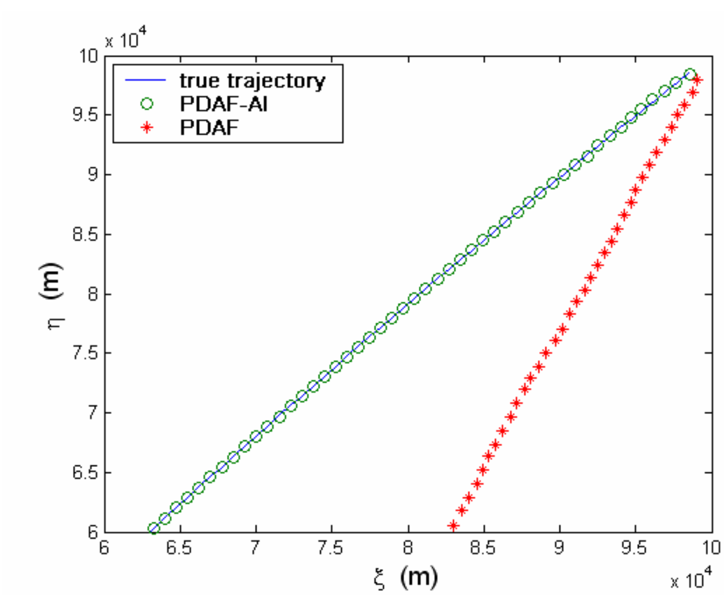

Figure 3: Example of track with $\rho = 10\, dB$, clutter density $\lambda = 5\times 10^{-6}\, m^{-2}$, number of sensors: 1.

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 [5].

The in-track percentage for various system parameters is shown in Table 1. A simulation is judged as in-track if at the 100^{th} scan, the total number of validated measurements in the validation gate [5] 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 ($\lambda = 5\times10^{-6}\ m^{-2}$).

In Table 2, the results of early Monte Carlo simulations of the tracking performance in terms of root mean square error (RMSE) are listed. It was anticipated that in most situations, the PDAF-AI would exhibit a lower RMSE error than the PDAF. However, from the results in Table 2, it cannot be readily concluded that PDAF-AI for the two sensor case is necessarily better. For instance, it appears that tracking performance is better only about half the time using PDAF-AI. The explanation here is that only the results from the “in-track” simulation runs were included in calculating the RMSE.

Consequently, for the PDAF, since the in-track percentage is low, only a small number of simulation runs, where the target is relatively easy to track, are used to calculate the RMSE. The more difficult simulation runs, where the PDAF cannot keep track of the target, were excluded from the computation of the RMSE.

Table 1: In-track percentage for various situations.

$\rho\,(dB)$	$\lambda\,(m^{-2})$	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.

$\rho\,(dB)$	$\lambda\,(m^{-2})$	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

5.1 Conclusions and additional observations

From the computed results, it appears that the PDAF-AI is a promising approach for this application. It can exhibit very robust performance, even when the SNR is as low as 5 dB and the clutter density is very high. By utilizing data from multiple sensors, the performances of the tracker, both in terms of in-track percentage and RMSE, can be improved significantly. The above example shows that, even with the help of very simple signal amplitude features, the system can achieve a much better performance for data association and target tracking.

Also, for the PDAF-AI, due to its superior capability in discriminating the target from clutter and to keep track of the target, more "in-track" simulation runs, which include both the relatively easy-to-track cases (where the RMSE is calculated for the PDAF) and the difficult cases, are employed in calculating the RMSE. Therefore, some of the results in Table 2 above show that PDAF is better in terms of the RMSE for the in-track runs. Again, this is not a very fair comparison, because in calculating the RMSE of the PDAF-AI, some hard-to-track simulation runs are included, in which the PDAF loses track of the target, whereas the PDAF-AI continues to keep target track. In these hard-to-track Monte-Carlo simulation runs, the accuracy of the target tracking (state estimation) tends to be much larger than that in the easy-to-track simulation runs. So incorporating results from these runs may degrade the overall RMSE.

In any case, more simulations are necessary 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. More extensive performance evaluations are underway by the authors to confirm expected trends.

6. 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 low false alarm rate. Multiple radars were assumed to operate together in a non-interference limited manner. A two-fold approach was discussed: (1) measuring and processing radar returns in a shared manner for target feature extraction based on waveform diversity techniques; and (2) 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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