Sensor Fusion for Target Detection and Tracking

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Abstract

Multi-path can be a significant contributor to poor detection performance in radar ground moving target tracking systems. Recently, ground multi-sensor networks have been used to detect and track targets. Unfortunately, such networks can only be deployed in a limited area compared with the coverage possible using a radar. We thus show how in those areas where multipath contributes to detection errors how the ground sensor network can improve performance.

1. Introduction

We will first describe our radar system and how our phased array UHF tracking system is subject to multi-path in tracking near a double chain-link fence line. We show our detection performance using a spectral matched filter tracking vehicles between this fence. We then will describe our ground sensor network in terms of N sensors each with independent detection statistics and independent noise conditions. Finally we will show the improved detection performance with our sensor network also deployed between the fence line to augment our radar system.

2. Radar Data Model

We first describe the structure of the spectral data model used for representation of signals within the multipath area. This model allows representation of the complex signal and noise processes due to the radar reflections in the multipath area. Such representation allow some separation of the target model vs. the interference model before applying an adaptive matched filter. In order to decompose a signal we use the standard Mallat dyadic decomposition [3] shown in Figure 1.

A Kth order model [3] defined on the Mallat multiresolution structure is defined in either with $t \in \{1, 2, \ldots, K(T+1)\}$. Such a structure for 1D signals takes the form of a binary tree structure.To represent this Markov [1,2] random field we define a given node in the binary tree structure as s, its parent node as $s\bar{\gamma}$ where $\bar{\gamma}$ shifts the wavelet coefficients from parent $s\bar{\gamma}$ to child s shown in Figure 2. Now if we have the random variable Z representing the current state of any Γ_s at any stage of the tree in either 1 or 2 Dimensions then we insert our local scale iterative relationship, the basic probabilistic Markov relationship is defined as

$$p_{Z_t,\, t \in \Gamma_{s\alpha_i} | Z_T,\, T \in \Gamma_s}(Z_t, t \in \Gamma_{s\alpha} | Z_T, T \in \Gamma_s) =$$

$$p_{Z_t,\, t \in \Gamma_{s\alpha_i} | Z_T,\, T \in \Gamma_{s,i}}(Z_t, t \in \Gamma_{s\alpha} | Z_T, T \in \Gamma_{s,i}) \qquad (1)$$

3. Radar Detection Performance

Given that we have defined the radar multi-resolution model and a representative wavelet Markov structure we now define a test statistic that conforms to our model [1]. If we let s̲ be the Markov complex vector of target reflectivity, n̲ a Markov clutter plus noise vector and x̲ equals the combined signal vector.

$$\underline{x} = \underline{s} + \underline{n} \qquad (2)$$

We now define the expected value of the x̲ to be the hypothesis H_0 in the presence of no target and H_1 to be the expected value of x̲ in the presence of the target. Additionally, if we define the covariance of the noise/clutter Markov vector as M we have

$$E\{\underline{x}|H_0\} = 0, \quad E\{\underline{x}|H_1\} = \underline{s}, \quad E\{nn^h|H_i\} = M \qquad (3)$$

We thus define the matched filter detection test statistic given Markov signal and noise estimates as follows:

Proceedings of the 31st Applied Imagery Pattern Recognition Workshop (AIPR'02)
0-7695-1863-X/02 $17.00 © 2002 **IEEE**

$$|y| = \frac{\left|\underline{s}^h M^{-1} \underline{x}\right|}{\sqrt{\underline{s}^h M^{-1} \underline{x}}} \quad \begin{matrix} \leq \mu & \text{then } H_0 \\ > \mu & \text{then } H_1 \end{matrix} \qquad (4)$$

A target is judged to be present if the test statistic |y| is greater than threshold μ and judged to not be present if less than the threshold. Note that with appropriate pruning of coefficients the model order of the covariance matrix M is significantly reduced thereby reducing the overall complexity of the detection calculation. Thus our Markov incremental approach to data ordering allows us to construct an order to prioritize the coefficients that allows minimal degradation in detection performance as model order is reduced. This process is much the same as conventional compression techniques that gradually decrease image quality with coefficient removal.

4. Sensor Network Detection Model

Our goal is to minimize the global minimum probability of error [4,5] of our sensor network shown in Figure 2 by minimizing

$$C(\alpha, k) = P_F - P_D = -\int_{P_f(\alpha)}^{P_d(\alpha)} \frac{x^{k-1}(1-x)^{N-k}}{B(k, N-k+1)} dx \qquad (5)$$

where $C(\alpha, k)$ is the total error metric combining both probability of false alarm and probability of detection and

$$B(a, b) = \int_0^1 x^{a-1}(1-x)^{b-1} dx \qquad (6)$$

is the complete Beta function, P_F is the probability of false alarm and P_D is the probability of detection, P_f and P_d is are the local probabilities at each sensor. k is the number of local decisions such that $u_i = 1$ required for the fusion processor to make the global decision $u = 1$, α is the threshold of the local processors. The optimal solution of equation 5 requires optimization over the discrete parameter k. For a given k, the best α is given by the solution to

$$\alpha_k = \left[\frac{1-P_f(\alpha_k)}{1-P_d(\alpha_k)}\right]^{N-k} \left[\frac{P_f(\alpha_k)}{P_d(\alpha_k)}\right]^{k-1} \qquad (7)$$

This optimization applies regardless of the fusion rule applied to the sensors.

5. Test Results

We used a 5 element simulated seismic sensor array in conjunction with the UHF radar to detect vehicles in the multipath area. Vehicles are detected simply by taking peak values from the signal output of the seismic sensors. We apply our joint optimization criteria to our sensor network distributed at 15 foot intervals along the road in our multi-path area as described in equation 7. The results are shown in Figure 3. We see that the radar has a high probability of detection but also an extremely high probability of false alarm due to the multi-path. The sensor network has a poor probability of detection but an extremely good probability of false alarm. Integrating the two sets of sensors using a fusion rule which averages the outputs of each type of sensor we see that we significantly reduce the probability of false alarm of the radar network while not significantly reducing the probability of detection.

6. Conclusion

Using integrated radar and ground sensor networks significantly improves the detection performance of radar targets in a multi-path environment. Such improvement in performance has implications for using more varied type of sensors to support the radar with statistics that complement the radar's receiver operating characteristic.

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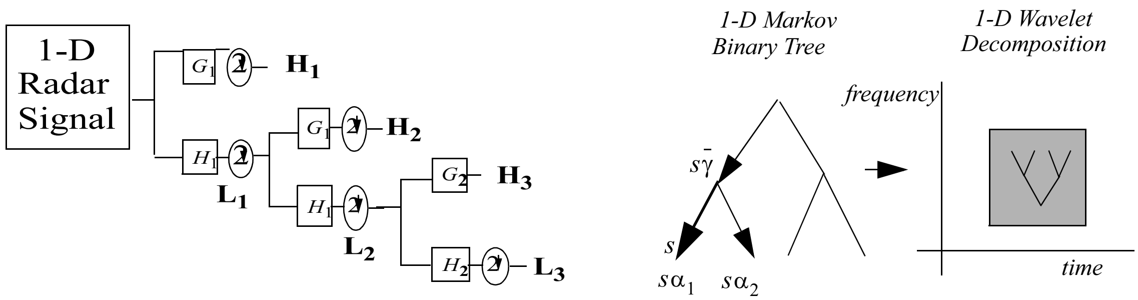

Figure 1: Mallat Dyadic Decomposition and Wavelet Markov Structure

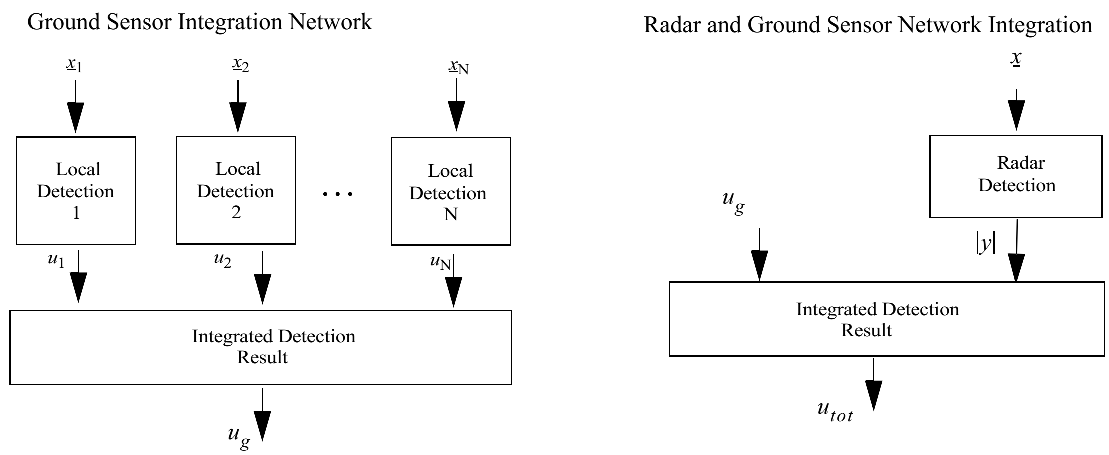

Figure 2: Ground Sensor Network and Integrated Radar Detection

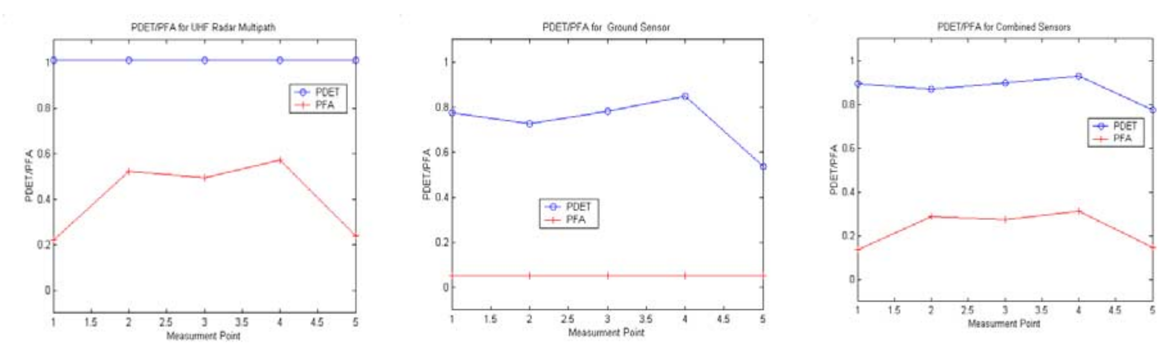

Figure 3a,b,c Radar Detection Results, Sensor Network Detection Results, Integrated Detection Results

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