A Spectral Approach to Image-Enhanced Moving Target Radar Detection

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Abstract–A difficult problem with ground moving target radar (GMTI) detection is how to consistently track targets moving through non-homogeneous regions of clutter such as forest and urban boundaries. Although attempts have been made to mitigate this detection problem using terrain mapping data, such data does not give current clutter information due to change in vegetation, roads, buildings, and seasonal variation. We propose to use synthetic aperture radar (SAR) imagery to enhance the detection performance of GMTI radar. We will use a multiresolution Markov model to represent both target and background clutter. This multiresolution structure will allow us to accurately match GMTI clutter with the geographically registered SAR imagery for consistent moving target detection through clutter boundary areas.

I. Introduction

We first start by showing the detection process and how we select image regions to model the clutter in the GMTI test cell. We then show how to represent both target and clutter radar returns in terms of the multiresolution radar structure. We then will show how the multiresolution Markov structure will allow us to integrate moving target radar returns with synthetic aperture imagery for enhanced detection performance.

II. Detection scheme

We now define a test statistic used in our moving target detection model. We let $\underline{s}$ be the complex vector of target reflectivity, $\underline{n}$ a clutter plus noise vector, and $\underline{x}$ equals the combined signal vector.

$$\underline{x} = \underline{s} + \underline{n} \tag{1}$$

We now define the expected value of the $\underline{x}$ to be the hypothesis H_0 in the presence of no target and H_1 to be the expected value of $\underline{x}$ in the presence of the target. Additionally, if we define the covariance of the noise/clutter vector as M we have

$$E\{\underline{x}|H_0\} = 0, \quad E\{\underline{x}|H_1\} = \underline{s}, \quad E\{nn^h|H_i\} = M \tag{2}$$

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

$$|y| = \frac{|\underline{s}^h M^{-1} \underline{x}|}{\sqrt{\underline{s}^h M^{-1} \underline{x}}} \quad \begin{matrix} \le \mu & \text{then } H_0 \\ > \mu & \text{then } H_1 \end{matrix} \tag{3}$$

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. As is shown in Figure 1 we will use the radar image information to define the relative locations of clutter that resemble that in the moving target test cell.

We denote the clutter in the GMTI data as n_{cm}, the clutter in the test cell in the moving target radar data is n_{tm}, and the target in the test cell is s_{tm}. Thus

$$\underline{x}_{tm} = \underline{s}_{tm} + \underline{n}_{tm} \tag{4}$$

Additionally we designate the clutter in the test cell in the radar image as n_{ti} and the radar clutter in the matched clutter in the image cell as n_{ci} We will use the SAR data to model the background clutter in the the GMTI data such that we will find the geographic location of the GMTI data that best represents the clutter in the GMTI test cell as is shown below

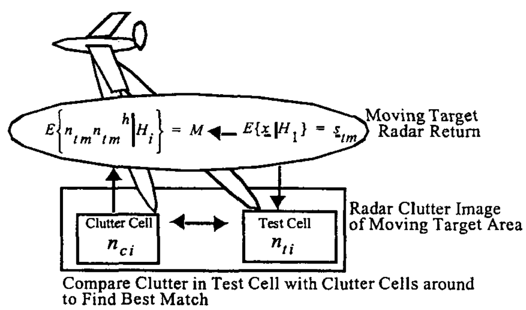

Fig. 1 Clutter Detection Scheme

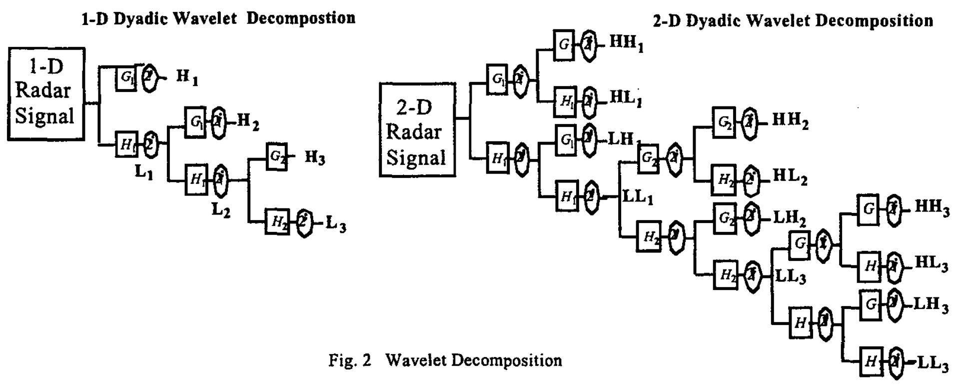

Fig. 2 Wavelet Decomposition

Given that our SAR imagery may not have the same resolution as the GMTI we must somehow make the radar imagery resemble in resolution what the moving target radar sees. In order to do this, we use a multiresolution spectral model for radar reflectivity and apply this model to clutter selection.

III. MULTIRESOLUTION MARKOV RADAR SIGNAL

In the development of radar reflectivity we will assume linear FM transmission of signals with standard far field assumptions . Gorman and Subotic [3] show that a complex valued radar signal taking into account resolution ρ, $T(\underline{x}_j;\rho)$, is an independent increments process in resolution

$$E\left\{[T(\underline{x}_j;\rho_2)-T(\underline{x}_j;\rho_1)][T(\underline{x}_j;\rho_3)-T(\underline{x}_j;\rho_2)]^*\right\} = 0 \quad (5)$$

for $\rho_1 < \rho_2 < \rho_3$. Under this condition the variance of the difference process of T is made constant, it can be shown shown that the resolution step size $\delta\rho_i$ is then

$$\delta\rho_i = \frac{\gamma\rho_i^2}{1-\gamma\rho_i} \quad (6)$$

Using equation 6 we can use a dyadic resolution sampling which means the values of $\gamma = 2^n$ where n is the relative wavelet scale. Such dyadic sampling does not always give resolutions exactly matched to the GMTI radar but is more efficient to implement than continuous sampling for the SAR data. We now apply a dyadic wavelet transform as in [5] to both the moving target radar data and the radar imagery to extract the multiresolution radar model as is shown in Figure 2. We use define a nth order Markov structure on the multiresolution structure in one and two spatial dimensions as described by Luettgen and Willsky in [4]

Such a structure for 1D signals takes the form of a binary tree structure as is shown in Figure 3. To represent this Markov 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. To represent a 2-D Markov random field we define a given node in the quad tree structure as S, the children nodes as $S\alpha_{NW}, S\alpha_{NE}, S\alpha_{SE}, S\alpha_{SW}$ and the

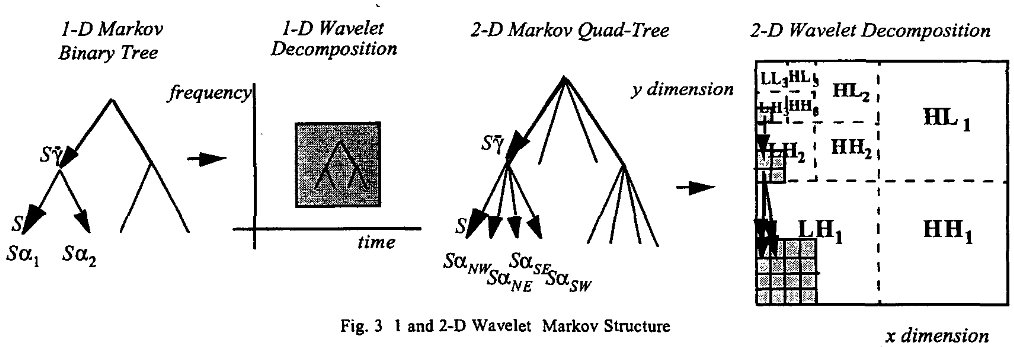

Fig. 3 1 and 2-D Wavelet Markov Structure parent node as $S\bar{\gamma}$ where as in the 1-D case $\bar{\gamma}$ shifts the wavelet coefficients from parent $S\bar{\gamma}$ to child S.

IV. Integrated Detection Process

In order to accurately model the 1-D radar clutter using the 2-D image with the Markov structure we first must geographically register both sets of data to the same range and aspect angle. We then transform both the moving target radar return and the radar image using a dyadic wavelet transform. We denote our GMTI clutter and SAR clutter cells in terms of the return signal from the target as

$$n_{cm} = T(x, \rho_{cm}) = [w_1, w_2, w_3 \ldots] = [S\bar{\gamma}, S\alpha_1, S\alpha_2 \ldots] \quad (6a)$$

and

$$n_{ci} = T(x, \rho_{ci}) = [w_1, w_2, w_3 \ldots]$$
$$= [S\bar{\gamma}, S\alpha_{NE}, S\alpha_{NW}, S\alpha_{SW}, S\alpha_{SW} \ldots] \quad (6b)$$

After making sure that the spatial frequencies of the radar image and moving target data are scaled appropriately we prune wavelet image coefficients such that

$$\rho_{ci} = \rho_{cm} \quad (7)$$

We then select the location of the optimal clutter cell denoted $\hat{n}_{ci}$ that matches the radar test cell in resolution using an autoregressive matching procedure described in [3] such that:

$$\hat{n}_{ci} \approx n_{ti} \quad (8)$$

Finally we find the corresponding clutter cell in the moving target data denoted $\hat{n}_{cm}$ that is co-registered with the clutter cell in the 2-D image such that.

$$\hat{n}_{ci} \Rightarrow \hat{n}_{cm} \quad (9)$$

Inserting $\hat{n}_{cm}$ into the last part of equation 2 as is described in for the radar imaging case in [1,6] we have

$$E\left\{\hat{n}_{cm}\hat{n}_{cm}{}^{h} \middle| H_i\right\} = \widehat{M}_{cm} \quad (10)$$

We denote the final detection equation as

$$|\gamma| = \frac{\left| \underline{s}_{tm}{}^{h}\widehat{M}_{cm}{}^{-1}\underline{x}_{tm} \right|}{\sqrt{\underline{s}_{tm}{}^{h}\widehat{M}_{cm}{}^{-1}\underline{x}_{tm}}} \begin{array}{l} \le \mu \text{ then } H_0 \\ > \mu \text{ then } H_1 \end{array} \quad (11)$$

This process is repeated for each new scan of the moving target and shows considerable improvement over non-image assisted tracking as is shown in the following results.

V. Results

The following tests in Figures 4 and 5 use the above spectral detection approach without and with imagery enhancement. A simulated SAR image and GMTI target was created using the multiresolution model described in [3] with two clutter regions. Tests were developed over a range of SNRs with the GMTI target moving from one clutter region to another. Using the clutter matched imagery, preliminary probability of detection and probability of false alarm results averaged at each SNR as the target moved across clutter boundaries are dramatically better due to the more accurate clutter modeling of the imagery.

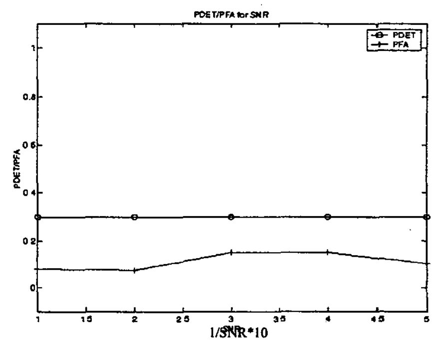

Fig. 4 Detection performance without imagery enhancement.

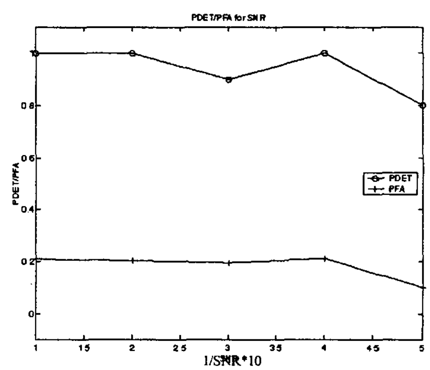

Fig. 5 Detection performance with imagery enhancement.

VI. Conclusion

Our preliminary results have shown that the multi-resolution-Markov model can be used to integrate GMTI and SAR imagery data to provide improved GMTI radar detection. Such integration of moving target and static background information is promising for extension to other wavelengths of imagery and other tracking data. This model should prove to be useful in integrating a number of remote sensing functions.

References

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