MULTISPECTRAL TARGET RECOGNITION USING ADAPTIVE RADAR AND INFRARED DATA INTEGRATION

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ABSTRACT

We report a RF and IR data-integration strategy based on a probabilistic (or a distribution) model. At the heart of our approach is the ability to extract the probability density functions (pdfs) from the sensed dataset for RF and IR respectively followed by the detection or target identification process based on posterior fusion (i.e., the product of individual pdfs) and Bayesian decision process. The pdf-acquisition processes in RF and IR modules have been further refined with clutter models and data-compression techniques.

Index Terms— Data integration, Multispectral target recognition, Posterior fusion, Data compression

1. INTRODUCTION

Data fusion techniques provide a powerful toolset capable of addressing a broad range of remote sensing problems for both military and civilian applications. Originally, the use of fusion techniques provided a statistical edge over single sensor data in the same-source domain. In recent years, data fusion has been designed to merge different sensors or sensing modalities in order to improve detection and classification accuracies compared to systems that utilize a single sensor. Each of these data sources possesses inherent strengths and weaknesses in isolation. Through careful combination, these fusion techniques exploit the collective data in order to mitigate their respective weaknesses or vulnerabilities. For example, radar or RF sensor can accurately measure the range of an object. On the other hand, IR sensor can detect the emissivity of an object but cannot measure its range. The effective utilization of both sensor types provides missing information on either side and allows the simultaneous location of an object as well as its intrinsic properties. This results in improving the accuracy of determining the identity of an object.

2. RF AND IR DATA-INTEGRATION STRATEGY BASED ON A PROBABILISTIC MODEL

The detail of entire data-integration process is provided as follows. First, the sensed data in RF and IR modules are processed through independent paths as shown in Fig. 1. Before proceeding further, it is to be mentioned that we assume two states (S_1 = "*No target*" and S_2 = "*Target present*") for each sensor domain and obtained priors. The pdf information together with priors is also fed into the Bayesian process. Upon receipt of all the information from both RF and IR modules, the posterior fusion is performed by making a product of individual pdfs as well as priors for each state. Subsequently, the Bayesian decision rule is applied to the fusion results, identifying the target state as well as generating following four probability metrics (1) Prob. of target being identified, (2) Prob. of no target, (3) Prob. of missed target and (4) Prob. of false alarm.

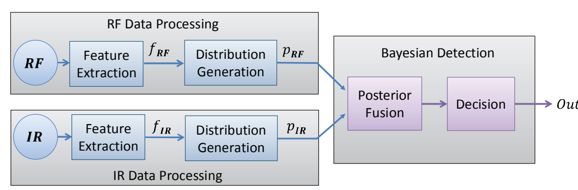

Fig. 1. RF and IR data integration using Bayesian method

3. ILLUSTRATIVE EXAMPLE

In the RF module, the received data from a target is transformed into Fourier domain for extracting Doppler features. Typically radar returns from moving targets are distributed into a spectrum through the Doppler effects. The time-varying Doppler signatures at the selected Doppler bin can fall in Rayleigh distribution, which may vary depending on the signal-to-noise ratio [1]. The pdfs corresponding to the Doppler signatures are then identified and sent to the Bayesian estimator along with priors. In the IR module, the threshold region is set by the user based on the given knowledge (e.g., intensity) of object(s) of interest. The captured image(s) is then thresholded into the binary image and pixels satisfying the threshold region are counted, so that the number of counted pixels becomes an extracted IR feature. The binomial distribution is selected as an IR pdf and specified as a function of number of pixels. Our preliminary results illustrating our entire data-integration process are summarized in Table 1, showing the significant improvements. Notably, probabilities of missed target and false alarm using fusion are improved by at least 15% than those using single domain.

Probability Metric	RF Only	IR Only	Fused RF & IR
No Target	.9910	.9900	.9914
Target	.3930	.7288	.8321
Miss Rate	.6069	.2712	.1678
False Alarm	.0088	.0100	.0084

Table 1. Example of Bayesian RF and IR data integration. Notable improvements using fusion technique are observed as highlighted in red.

4. ADAPTIVE DATA-INTEGRATION STRATEGY BASED ON REFINED DATA-PROCESSING

To realize the practical pdfs, currently we have been refining the pdf-acquisition processes in both RF and IR modules as illustrated in Fig. 2. In the RF module, it is important to include the stochastic characteristics of scattering coefficients from the target and clutter. The scattering coefficients of the deterministic target will be simulated using the commercial electromagnetic (EM) simulation tool [2]. In addition, the clutter can be investigated by empirical terrain clutter models or analytic theories of rough surface scattering, which are efficient in terms of computational requirements [3-5]. Since the Doppler signatures need to be addressed in this research, phase and geometrical factors associated with the target position and orientation also should be carefully considered in the simulations. We can also consider the moving target indication (MTI) filter that can suppress the clutter in the Doppler frequency domain in the RF module. It could enhance the probability of detection for extracting the features from small and slow moving targets [6, 7]. In the IR module, we would like to extract and incorporate more features in order to render pdfs. Features that we will employ are multiband data (*n* band slices) of a target finding mean and variance over a spectral range. The mean and variance from the data will directly specify the peak location and width of pdfs. Also we will incorporate the band-selection algorithms (data-compression techniques [8,9]) at the data acquisition stage to identify only the minimal and relevant bands for extracting multiband features eliminating data redundancy.

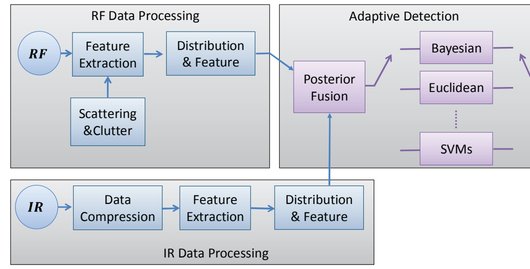

Fig. 2. Refined RF and IR data-integration strategy

Finally, we also intend to extend the functionality of our strategy beyond Bayesian detection to perform target classification using proven techniques such as Euclidean or Mahalanobis classifiers and support vector machines (SVMs) [10].

5. REFERENCES

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