Multisensor Joint Fusion and Detection of Mines Using SAR and Hyperspectral

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Abstract—In this paper a new nonlinear joint fusion and detection algorithm is proposed for locating anomalies from two different types of sensor data (synthetic aperture radar (SAR) and Hyperspectral sensor (HS) data). The proposed approach jointly exploits the nonlinear correlation or dependencies between the two sensors in order to simultaneously fuse and detect the objects of interest (mines). A well-known anomaly detector, so called RX algorithm is extended to perform fusion and detection simultaneously at the pixel level by appropriately concatenating the information from the two sensors. This approach is then extended to its nonlinear version using the idea of kernel learning theory which implicitly exploits the higher order dependencies (nonlinear correlations) between the two sensor data through an appropriate kernel.

I. INTRODUCTION

The recent availability of accurately geo-located, multi-sensor data (collected as part of the Wide Area Airborne Mine Detection (WAAMD) program) has created unprecedented opportunities for the exploration of multi-sensor, target detection algorithms. The main purpose of this paper is to nonlinearly fuse the information contents in hyperspectral and SAR imagery to effectively detect targets of interests (both buried and surface mines). Because of the significant differences in basic physical properties and signal dimensionality between these two sensors, fusion of the raw or processed data from these sensors might mitigate the false alarm rate significantly for anomaly detection purposes.

We extend a well-known anomaly detector so called RX algorithm [1] to perform fusion and detection simultaneously at the pixel level by appropriately concatenating the data from the two sensors. By concatenating the data from the two sensors the RX algorithm exploits the linear correlation between the two sensor data. This approach is then extended to its nonlinear version using the kernel RX algorithm [2]. The nonlinear joint fusion/detection approach is based on the ideas in the statistical kernel learning theory [3] which implicitly exploits the higher order dependencies (nonlinear correlations) between the two sensor data through an appropriate kernel function.

This paper is organized as follows. Section II introduces the RX algorithm and its extension to operate on two sensor data simultaneously. Section III introduces the idea of kernel learning theory and kernel trick. In section IV the nonlinear kernel-based RX algorithm is described for jointly detecting anomalies on SAR and HS data. In section V we report the performance of linear and nonlinear joint fusion/detection RX algorithm on co-registered SAR and hyperspectral imagery. Conclusion is given in section VI.

II. RX ALGORITHM FOR JOINT FUSION AND DETECTION

In the proposed approach, fusion and detection is done at the pixel level by concatenating the HS data with the high resolution SAR data and processing the concatenated data by an anomaly detector. This approach jointly exploits the linear (nonlinear) correlation or dependencies between the two sensors in order to simultaneously fuse and detect the objects of interest. In [1] a spectral anomaly detection algorithm was developed for detecting targets of unknown spectral distribution against a background with unknown spectral covariance. This algorithm is now commonly referred to as the RX anomaly detector which has been successfully applied to many hyperspectral target detection applications. It is now considered as the benchmark anomaly detection algorithm for multispectral/hyperspectral data. The RX-algorithm is a constant false alarm rate (CFAR) adaptive anomaly detector which is derived from the Generalized Likelihood Ratio Test (GLRT). The RX algorithm is based on exploiting the difference between the spectral signatures of an input pixel with its surrounding neighbors (or background pixels). This distance comparison is very similar to the Mahalanobis distance measure which is calculated by comparing the corresponding wavelengths (spectral bands) of two measurements. The RX algorithm assumes that the covariance of the background clutter is unknown which is calculated from the data. In the conventional RX algorithm, a non-stationary local mean is subtracted from each spectral pixel. The local mean \( \mu_b \) is obtained by sliding a double concentric window (a small inner window region (IWR) see Fig. 1) over every spectral pixel in the image and calculating the mean of the spectral pixels falling within the outer window. The size of the inner window is assumed to be the size of the typical target of interest in the image. The residual signal after mean subtraction is assumed to approximate a zero-mean pixel-to-pixel independent Gaussian random process.

Let each observation spectral signal consisting of J spectral bands be denoted by \( x(n) = (x_1(n), x_2(n), ..., x_J(n))^T \). Define \( X_b \) to be a \( J \times N \) matrix of \( N \) centered (mean-removed) reference background clutter pixels (or pixels in the outer window). Each observation spectral pixel is represented as a column in the sample matrix \( X_b = [x(1), x(2), ..., x(N)] \). Consider a test pixel \( r_{ij} \) at pixel location \( ij \), the RX-algorithm output at each pixel is give by
\[ \delta_{\text{ex}}(r_j) = (r_j - \hat{\mu}_b)^T \hat{C}_{bb}^{-1}(r_j - \hat{\mu}_b), \]  

(1)

where \( r_j \) represents the pixel under consideration located at the center of the OWR, \( \hat{\mu}_b \) represents the estimated mean of the pixels within the OWR, and \( \hat{C} \) is the estimated covariance matrix of the pixels within the OWR given by \( \hat{C} = (1/N) X_hX_h^T \).

Figure 1. A sliding dual window: an inner window region (IWR) and an outer window region (OWR).

If the dual window is placed within a spatially homogeneous region consisting of similar types of materials, such as natural backgrounds, the statistical characteristics of the IWR and OWR will be similar to each other. However, the IWR and OWR will contain significantly different statistical characteristics if the dual window is centered on a region where the target is surrounded by the local background. Use of an appropriate threshold on the RX output (Eq. (1)) it allows most targets to be detected as anomalies.

The dual window RX-algorithm (1) is easily applied to each HS pixel since these pixels are already in vector form. However, in the case of high resolution SAR each co-registered HS pixel corresponds to a block of pixels in the SAR image due to the difference in spatial resolution between the SAR and HS. For SAR imagery we group all the pixels that physically correspond to a single HS pixel and represent them as a SAR vector pixel. This process is done for each corresponding HS pixel in order to form a SAR cube image of the same spatial resolution as HS image. It should be noted that the number of corresponding SAR pixels to each HS pixel will obviously be different from the number of spectral bands in HS. The RX algorithm can now be applied separately to the HS and SAR cubes of the same resolution to obtain the anomalies from each sensor data independently.

To develop an RX like joint fusion and anomaly detection algorithm, let each pixel located at \((i, j)\) in the HS image be represented by a vector \( x_h(i, j) \) consisting of \( J \) spectral bands and the corresponding block of SAR pixels centered at \((i, j)\) be represented by \( x_s(i, j) \) consisting of \( P \) pixels since for practical platforms the SAR image has much higher resolution than the HS sensor. Furthermore, let the concatenated vectors from the two sensors corresponding to the same HS pixel location \((i, j)\) after normalization (by removing the mean and dividing by the maximum value for each sensor data separately) be represented by a partition vector \( x_{hs}(i, j) = \begin{bmatrix} x_h(i, j) \\ x_s(i, j) \end{bmatrix} \) where \( x_h(i, j) \) and \( x_s(i, j) \) are the pixels under consideration at the center of the dual window in the HS and SAR images, respectively. Applying the RX algorithm on the concatenated data \( x_{hs}(i, j) \) is given by

\[ \delta_{\text{ex}}(i, j) = \begin{bmatrix} x_h(i, j) \\ x_s(i, j) \end{bmatrix}^T \left( \begin{bmatrix} \hat{\mu}_h \\ \hat{\mu}_s \end{bmatrix}^{-1} (\hat{C}_{hh}^{-1} + \hat{C}_{ss}^{-1}) \right)^{-1} \begin{bmatrix} \hat{\mu}_h \\ \hat{\mu}_s \end{bmatrix} - \begin{bmatrix} x_h(i, j) \\ x_s(i, j) \end{bmatrix}. \]  

(2)

where \( \hat{\mu}_h \) and \( \hat{\mu}_s \) are the estimated means of all the pixels \( x_h \) and \( x_s \) in the corresponding outer-windows, \( \hat{C}_{hh} \) and \( \hat{C}_{ss} \) are the estimated covariance matrices of the HS and SAR data, respectively. In (2) the linear correlation between the HS and SAR data is exploited through the inverse covariance matrix of the concatenated data. If the SAR data is not linearly correlated to the HS data \( \hat{C}_{hs} = \hat{C}_{sh} = 0 \) in (2) then the joint fusion and detection algorithm is the same as performing RX on each sensor data separately and adding the two output results.

Let the inverse covariance matrix so called the precision matrix be represented as

\[ \hat{C}^{-1} = \begin{bmatrix} \hat{C}_{hh}^{-1} & \hat{C}_{hs}^{-1} \\ \hat{C}_{sh}^{-1} & \hat{C}_{ss}^{-1} \end{bmatrix} = \begin{bmatrix} \hat{\Lambda}_{hh} & \hat{\Lambda}_{hs} \\ \hat{\Lambda}_{sh} & \hat{\Lambda}_{ss} \end{bmatrix}, \]  

(3)

Now the RX output can be expanded into four independent terms

\[ \delta_{\text{ex}}(i, j) = (x_h(i, j) - \hat{\mu}_h)^T \hat{\Lambda}_{hh}(x_h(i, j) - \hat{\mu}_h) + (x_s(i, j) - \hat{\mu}_s)^T \hat{\Lambda}_{ss}(x_s(i, j) - \hat{\mu}_s) \]  

\[ + (x_h(i, j) - \hat{\mu}_h)^T \hat{\Lambda}_{hs}(x_h(i, j) - \hat{\mu}_h) + (x_s(i, j) - \hat{\mu}_s)^T \hat{\Lambda}_{sh}(x_s(i, j) - \hat{\mu}_s). \]  

(4)

The first and the fourth term are the RX output contributions from each sensor data with a joint precision matrix and the second term (or third term) is the contribution from the cross precision matrix. Output of each of these terms can be displayed as an image to see the cross contributions due to the two sensors.

III. KERNEL MAPPING

One way to exploit the higher order correlation between the two data is to explicitly map each sensor data into a higher dimension by a nonlinear mapping. For example, assume the input hyperspectral data is to explicitly map each sensor data into a higher dimension by a nonlinear mapping function \( \Phi: \mathcal{X} \rightarrow \mathcal{F} \)

\[ x_h(i, j) \mapsto \Phi(x_h(i, j)) \]  

(4)

where \( x_h(i, j) \) is an input vector which is mapped into a potentially much higher (and could be infinite) dimensional feature space. Any linear anomaly technique can now be remodeled into this high dimensional feature space by replacing the original input data \( x_h(i, j) \) with the mapped data.
\( \Phi (x_h (i, j)) = x_h \Phi (i, j) \). Due to the high dimensionality of the feature space, \( \mathcal{F} \), it is computationally not feasible to directly implement any algorithm in this feature space. However, the kernel-based learning techniques use an effective kernel trick given by

\[
k(x, y) = < \Phi (x), \Phi (y) > = \Phi (x)^T \Phi (y) \tag{5}\]

which implements a dot product between two vectors in the feature space by employing a kernel function \( k \) associated with the nonlinear mapping \( \Phi \). Using the kernel trick representation (5), it allows us to implicitly compute the dot products in \( \mathcal{F} \) without mapping the input vectors into \( \mathcal{F} \). Therefore, in the kernel methods, the mapping function \( \Phi \) does not have to be identified. A dot product in \( \mathcal{F} \) can be avoided and replaced by a kernel function, \( k \), a nonlinear function which can be easily calculated without identifying the nonlinear map, \( \Phi \). A preferred kernel to utilize is the Gaussian radial basis function (RBF) kernel:

\[
k(x, y) = \exp \left( -\frac{\| x - y \|^2}{\sigma} \right) \quad \text{where} \quad \sigma > 0 \text{ is a constant.}
\]

IV. NONLINEAR JOINT FUSION & DETECTION RX ALGORITHM

In [2] it has been shown how to extend the RX algorithm given by (1) to a nonlinear version (so called Kernel RX) by using the idea of kernel-based learning theory. The kernel version of the RX algorithm implementation and, perhaps, modification the concepts was exploited in our pixel-based fusion and detection algorithm. The nonlinear correlation between the SAR and HSI data fusion and detection was developed based on the kernel RX algorithm. The nonlinear function which can be easily calculated without identifying the nonlinear map, \( \Phi \). A preferred kernel to utilize is the Gaussian radial basis function (RBF) kernel:

IV. RESULTS

The hyperspectral mine image consists of 70 bands over the spectral range of 8—11.5 \( \mu m \), which includes the long-wave infrared (LWIR) band. The SAR images used were produced from a SAR sensor operating in the high and low frequency range. Fig. 2 shows the co-registered SAR and HS images, which contain surface mines and disturbed soil representing buried mines, respectively. We have implemented the RX-anomaly detector as well as the kernel RX to detect mines in SAR and HS images separately and on the concatenated SAR/HI data to obtain a joint fusion/detection algorithm. Fig. 2 (a) and (b) show the original HSI and SAR images of the same region that are processed, respectively. Fig. 3 shown all the ground truth mines overlapped on the HS image. Results of the RX algorithm and kernel RX are shown in Fig. 4 (a)-(d). Fig. 4 (e) and (f) show the joint linear and nonlinear fusion/detection results using the concatenated data and the ROC curves are represented in Fig. 5. It is clear from Fig. 5 that the nonlinear joint fusion/detection algorithm performance exceeds that of the linear RX as well as the single sensor results.

VI. CONCLUSION

In this paper, we have designed a nonlinear fusion algorithm for detection of surface and buried mines. A nonlinear pixel level joint fusion and detection was developed based on the kernel RX algorithm. The nonlinear correlation between the SAR and HSI data was exploited in our pixel-based fusion and detection algorithm. Use of different kernels as well as developing procedures for weighting the kernels is still to be investigated. With careful algorithm implementation and, perhaps, modification the concepts should be extensible to additional operational scenarios.

REFERENCES


Figure 2. (a) HS imagery (b) SAR imagery

Figure 3. Displays all the ground truth mines.

Figure 4. Shows (a) RX detected mines for HS, (b) RX detected mines for SAR, (c) kernel RX detected mines for HS, (d) kernel detected mines for SAR, (e) joint linear fusion/detection RX results and (f) joint nonlinear fusion/detection KRX results.

Figure 5. Shows the ROC plots for the conventional RX and kernel RX algorithms.