# Texture Segmentation Based Anomaly Detection in Remote Sensing Images

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***Abstract*—Anomaly detection is of great importance both in civil and military applications. To avoid the interference of complex background, we propose a texture segmentation based anomaly detection algorithm (TBAD). TBAD introduces the Gaussian Markov random field (GMRF) to model the distribution of background pixel values. Through the GMRF model, images are segmented into series of textures. And the conventional RX algorithm is applied on each segmented textures. Since TBAD can utilize both the spatial and the spectrum information of background, it can reduce the interference of complex background. Experiment applied to real image has validated the performance of the new approach.**

## I. INTRODUCTION

ANOMALY detection is of importance in a wide variety of applications including automatic target recognition (ATR), reconnaissance, surveillance, environmental monitoring, and agriculture, and has attracted great attentions in the past few decades [1][2]. The benchmark of anomaly detection is RX algorithm which is derived from the Generalized Likelihood Ratio Test (GLRT) with the assumption of Gaussian background [1]. However, background may be consisted of different ground cover types in real remote sensing images, such as water body, grass land, trees. This will lead to miss detection in complex background. Many researches attempt to use the Gaussian mixture model [3][4]. In reference [3], Ashton employs K-means cluster clustering the image into a number of statistical clusters and models each cluster with the Gaussian distribution. Subsequently, Carlotto proposes a similar approach using vector quantization to reduce the computational time [4] . However, the K-means based algorithm only considers the spectrum information of background. This will lead to miss clustering background pixels during the cluster process. In this paper, propose a texture segmentation based anomaly detection algorithm (TBAD). TBAD introduces the Gaussian Markov random field (GMRF) to model the distribution of background pixel values. By using GMRF model, images are segmented into series of textures. And the conventional RX algorithm is applied on each segmented textures. Since TBAD can utilize both the spatial and the spectrum information of background, it can reduce the interference of complex background.

## II. TEXTURE SEGMENTATION

Often images have different ground cover types of background. These differences of background should be considered respectively. One of the reasonable methods to model these background differences is texture segmentation method. Texture segmentation is also widely used in urban area classification and image interpretation. Among the most popular texture segmentation methods, the one based on the GMRF is used more widely. In this paper, we will introduce the GMRF to model the distribution of the background [5].

Let us consider a random field $X = \{x(s)\}_{s\in S}$, where $S$ is the set of pixels $s$. $x(s)$ is the random variable at site $s$, and $N_i$ is the neighboring set of $s$. A Gaussian Markov random field has the following property:

$$x(s) = \sum_{t\in N_i} \theta_t x(t) + \varepsilon(s) \tag{1}$$

Where $\theta_t$ are weight coefficients. In order to model texture features, the authors in [5] define a new matrix

$$\mathbf{A} = E[\boldsymbol{\alpha}(s)\boldsymbol{\alpha}^T(s)] \tag{3}$$

where $\boldsymbol{\alpha}(s) = [\alpha_1(s), \alpha_2(s), \cdots, \alpha_{k+1}(s)]^T$ is a vector

$$\alpha_i(s) = \begin{cases} x(s) & i = 1 \\ \sum_{t\in N_i} x_t & 0 < i \le k+1 \end{cases} \tag{2}$$

It can be derived that matrix $\mathbf{A}$ captures both the first and second moment information of the weight coefficients $\theta_t$ [5].

In fact, most remote sensing images are panchromatic images, multispectral images or even hyperspectral images. All these images have multi-bands data. Therefore, the above model must be extending to accommodate multi-bands data.

The model discussed above, can be readily extended to multi-bands images. For an image with $m$ color bands, we can define a $m \times m$ symmetric matrix $\mathbf{C}$

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_{1,1} & \mathbf{C}_{1,2} & \cdots & \mathbf{C}_{1,m} \\ \mathbf{C}_{2,1} & \mathbf{C}_{2,2} & \cdots & \mathbf{C}_{2,m} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{C}_{m,1} & \mathbf{C}_{m,2} & \cdots & \mathbf{C}_{m,m} \end{bmatrix} \tag{4}$$

Where

$$\mathbf{C}_{i,j} = E[[\boldsymbol{\alpha}^i(s) - \overline{\boldsymbol{\alpha}^i(s)}][\boldsymbol{\alpha}^j(s) - \overline{\boldsymbol{\alpha}^j(s)}]^T] \tag{5}$$

$\boldsymbol{\alpha}^i(s)$ is a vector defined by using data from the i-th band.

As discussed above, texture features are represented by the matrix $\mathbf{C}$. We consider the singular value decomposition (SVD) of $\mathbf{C}$ to extract texture features

$$\mathbf{C} = \mathbf{U}\mathbf{D}\mathbf{V}^T \tag{6}$$

Where $\mathbf{D}$ is a diagonal matrix whose diagonal entries are the singular values of $\mathbf{C}$, and $\mathbf{U}$ and $\mathbf{V}$ are unitary matrices.

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Let $d_1, d_2, \cdots, d_L$ be the singular values of $\mathbf{C}$ in descending order. Also, let the column of $\mathbf{U}$ associated with $d_i$ be $\mathbf{u}_i$. The texture feature vector is

$$\mathbf{f} = \sum_i \left( \frac{d_i}{\sum_{i=1}^{L} d_i} \right) \mathbf{u}_i \qquad (7)$$

Finally, we adopts stochastic expectation maximization (SEM) cluster to cluster the texture features vector.

In real multispectral or hyperspectral data the size of matrix $\mathbf{C}$ will be rather large. To save computational time, the Principal Component Analysis (PCA) is used to reduce the dimensionality of the data set.

After texture segmentation, the remote sensing image is segmented into series of textures.

$$X = \bigcup_{t=1}^{T} X_t \qquad (t = 1, 2, \cdots, T) \qquad (7)$$

Where $t$ is the index of the textures. Each texture can be modeled by a multivariate Gaussian distribution $X_t = \{\boldsymbol{\mu}_t, \boldsymbol{\Gamma}_t\}$ Where $\boldsymbol{\mu}_t$ and $\boldsymbol{\Gamma}_t$ are the mean and covariance of the $t$ th texture. The anomaly detection criterion is

$$d(\mathbf{x}_{i,j}) = \left[\mathbf{x}_{i,j} - \boldsymbol{\mu}_{t(i,j)}\right]^T \boldsymbol{\Gamma}_{t(i,j)}^{-1} \left[\mathbf{x}_{i,j} - \boldsymbol{\mu}_{t(i,j)}\right] \qquad (10)$$

$t(i, j)$ is the texture map which assigns an index to each pixel location based on its texture membership. $t(i, j) = t \mid \mathbf{x}_{i,j} \subset X_t$.

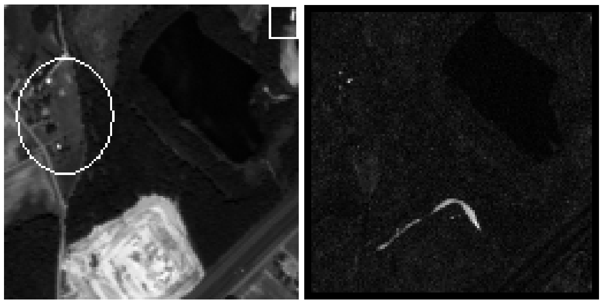
## III. Experimental Results

To assess the validity of the texture-based model, we apply both K-means based RX algorithm and TBAD to a portion of a real AVIRIS hyperspectral image from Low Altitude. We only use 40 bands images. The band images used are the 41st to 81st. The local statistical window size is 5×5. The neighboring system selected is the same as in [5]. Five subspace bases are preserved. The experimental results are shown in Fig.1.

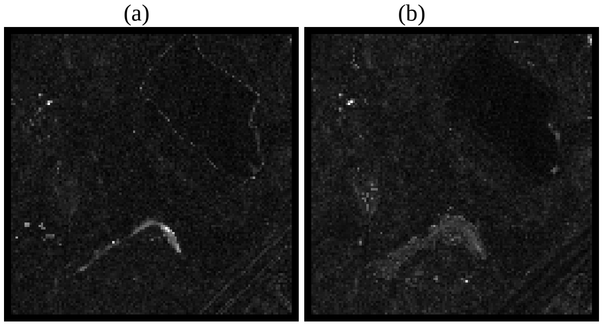
Figure 1 is detection results of RX algorithm, K-means based RX algorithm, and TDAD. RX algorithm is interfered by the edge of intensive fluctuation of background (Fig. 1b). K-means based RX algorithm can evidently reduce the interference of background (Fig. 1c). TDAD has the best detection results (Fig. 1d). The ROC curves (Fig. 1e) show that TBAD significantly outperforms RX algorithm and K-means based RX algorithm both at low and high false-alarm rates. This indicates that TBAD has the best detection performance among the entire evaluated algorithms.

## IV. Conclusion

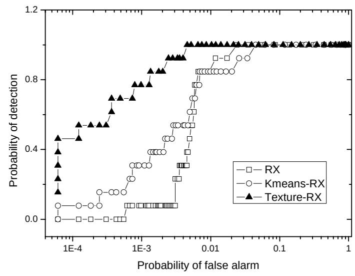
In this paper we present a new approach by using texture segmentation to model different cover types of background. Before detection process, our new algorithm segments image into series of textures and introduces the GMRF to model the distribution of background pixel values. For our new algorithm can utilize both the spatial and the spectrum information of background, it can reduce the interference of complex background.



(a) (b)



(c) (d)




(e)

Fig.1 Anomaly detection result (a) image of band 21st, (b) detection result of RX algorithm, (c) detection result of k-means based RX algorithm (d) detection result of texture segmentation based RX algorithm, (e) ROC curves

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