Target Detection Improvement in Hyperspectral Images

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Key words: Hyperspectral image, spectral Detection, spectral-spatial detection, ROC curves, error matrix **.**

SUMMARY

A complete modeling of a site may require information data such as a land cover. Hyperspectral airborne images represent the most appropriate source for the spectral analysis of land cover and the determination of surface materials**.**

Hyperspectral images have the high spectral resolution rather than to multispectral images. By development of remote sensing technology, the new sensors with hyperspectral capabilities in RS science will be replaced to multispectral imaging. A big advantage of hyperspectral images comparison to that of multispectral images is a continuous spectrum for each image cell that can be derived from image spectral measurement. Therefore, in this research these images have been used in detection process.

Conventional methods of target detection work only beased on spectral image data and features. To improve the accuracy of these spectral based target detection methods, the paper study usability of spatial correlation of spectral bands. Therefore, a combined spectral-spatial target detection method is suggested and evaluated based on ROC curves. As our previous experiments illustrated the CMFM is the most accurate sub-pixel detection algorithm; we apply it on spectral-spatial featuers of each image pixel. Our experiment results demonstrate a significant imporovment of accuracy for the suggested spectral-spatial target detection method.

چكيده

فنآوري سنجش از دور فراطيفي، در دو دهه گذشته پيشرفت چشمگيري داشته است. اين پيشرفت در طراحي و ساخت سنجندهها و همچنين در توسعه و پيادهسازي روشهاي پردازش دادهها، بسيار مشهود بوده است. در مقايسه با تصاوير چندطيفي، تصاوير فراطيفي داراي حدتفكيک طيفي بالاتري بوده از اين رو منحني طيفي مربوط به هر پيكسل نسبت به منحني طيفي پيكسلهاي تصاويرچندطيفي پيوستهتر ميباشد، بنابراين از تصاويرفراطيفي ميتوان به عنوان منبع مناسبي جهت نقشهبرداري مواد استفاده نمود.

پيچيدگي و حجم وسيع دادههاي حاصل از سنجندههاي فراطيفي باعث شده است كه امروزه روشهاي خبره و پيشرفتهتر آناليز دادههاي فراطيفي به منظور استخراج اطلاعات دقيقتر و كاملتر از آنها مورد توجه قرار گيرند. با توجه به حجم سنگين دادهها و پيچيدگي بالاي تصاوير فراطيفي، يكي از آناليزهاي اساسي براي نقشهبرداري مواد، شناسايي و آشكارسازي هدف است.

روشهاي متداول آشكارسازي هدف بر مبناي خصوصيات طيفي اطلاعات تصويري عمل مينمايند. ازاينرو در اين مقاله جهت بهبود دقت روشهاي آشكارسازي طيفي هدف از وابستگيهاي مكاني باندهاي طيفي استفاده شده است بر اين اساس يک روش آشكارسازي تركيبي طيفي-مكاني پيشنهاد شده و بر مبناي منحنيهاي ROC مورد ارزيابي قرار گرفت. آزمايشات پيشين صورت گرفته نشان ميدهد در بين الگوريتمهاي آشكارسازي هدف، الگوريتم CMFM داراي بالاترين دقت بوده از اين رو جهت بررسي روش آشكارسازي طيفي-مكاني از الگوريتم فوق استفاده گرديد كه بررسي-هاي انجام شده بهبود دقت قابل ملاحظهاي را نشان ميدهد.

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1. INTRODUCTION

During last two decades, hyperspectral remote sensing technology in which hundreds of spectral bands are collected has been a considerable progress. The progression is in the design and building of hyperspectral sensors and their data analyses methods (Varshney and Arora, 2004). In comparison with multispectral images, although high spatial and radiometric resolution of hyperspectral images have much higher capability to successful recognition of ground targets, some new problems appears. The first problem is high volume of data. it compels to prepare a high speed processing unit and use a high performance advanced algorithm. Nonetheless, it generally makes a long computation time (Homayouni and Roux, 2003). The second problem is low signal to noise ratio (SNR) in hyperspectral images. It is due to high sensitivity of hyperspectral sensors which acquire many unknown signals come from small complex unrecognizable objects with size less than spatial image resolution. Therefore, for enhance the accuracy of spectral target detection, the processing should be in subpixel level (Chang, 2003).

Target detection, classification, recognition and identification are various hyperspectral pattern recognition methods with different levels of user knowledge. There are also different data representation spaces including image space, spectral space and feature space. In this regard, there are different pattern recognition algorithms depending on selected level of user knowledge and representation space (Landgrebe, 1999).

One of the general hyperspectral image analyses is spectral target detection. In this paper, the target is a special material of building roofs that should be detected from aerial hyperspectral images. Material recognition of the building roofs is required to enhance the wave propagation model as a basis for designing mobile communication networks in urban areas (Homayouni and Roux, 2003). As buildings in urban area have high complexity from physical, geometrical and material point of views, high resolution hyperspectral aerial imagery has a high capability to building recognition and extraction.

Since two decades ago, several researchers have worked in spectral target detection subject. Chang and Heinz (2000) studied on three different algorithms of spectral target detection on AVIRIS images. Chang (2002) innovated Mahalanobis distance and adaptive filter as anomaly detection algorithms and evaluated them through AVIRIS images. Bakker (2002) also studied spectral angle and spectral distance methods as edge detection tools in HYMAP hyperspectral images. Homayouni and Roux (2003) compared three algorithms of spectral angle, spectral correlation, and minimum constrained energy. Lumme (2004) did recognition and classification of green covers through AISA images by spectral angle, spectral correlation and maximum likelihood algorithms. DU and Chang (2004) used spectral angle, spectral divergence information and their combination to do spectral detection on AVIRIS images. Negahbani (2006) studied on different algorithms of full-pixel and sub-pixel target detection.

He used HYMAP images to recognize mineral materials by these algorithms and evaluated them via ROC curves. Afary and Emami (2007) utilized two algorithms of spectral angle and maximum likelihood to detect and classify an hyperspectral image taken from a farming area.

In all researches, different spectral target detection methods have been developed and evaluated. The involved problem here is a significant level of target detection error. Therefore, different people have suggested various algorithms to reduce it. As it is mentioned, there are several reasons that cause to increase the target detection error including high volume of unknown receiving signals, sensor and atmospheric noises, high correlation of spectral bands, mixed pixels due to spectral overlapping and heterogeneity of object materials (Landgrebe, 1999). Therefore, for enhance the detection accuracy, this paper suggests two spectral-spatial target detection algorithms in which the spatial correlation of image pixels and their spectral data are used simultaneously in detection process.

2. BASICS OF SUGGESTED METHOD

This section first reviews the fundamental of our suggested spectral-spatial target detection algorithms. Then, outline of evaluation method based on ROC[1] curves that are described to make a background for evaluation of suggested algorithms.

2.1 Spectral Target Detection

So far various algorithms for spectral target detection are introduced. Each algorithm has some advantages and disadvantages. Therefore, if several algorithms are used together, it leads to more target detection accuracy. So in our previous research titled, Spectral Detection Improvement in Hyperspectral Image by using available Methods intelligent incorporation, 14 algorithms in three groups comprising deterministic measures, stochastic measures, and anomaly detection have been evaluated first and then fused (Akbari, Saadatseresht and Homayouni, 2008). There were four fusion methods including Boolean operator, Euclidean distance, fuzzy inference, and ANFIS. Regarding to this paper, in that research, we showed CMFM target detection algorithm has the highest accuracy. Therefore, in this paper, we utilize CMFM as a basis for suggested spectral-spatial target detection algorithms.

2.1.1 CMFM Target Detection Algorithm

Covariance-based Matched Filter Measure, CMFM, is one of the anomaly detection methods. The aim of anomaly detection is to search and find unknown targets with low probability of existence in the image. The anomaly detection works based on properties of covariance or correlation matrix of the target.

In equation 1, CMFM measures similarity of targets s_i and s_j (s includes spectral properties) after reducing their mean μ. More similarity value, means both targets are members of same class in higher probability (Chang and Chiang, 2002).

[1] Receiver Operating Characteristic

$$CMFM = (s_i - \mu)^T K_{L\times L}^{-1} (s_j - \mu) \qquad \text{Eq.1}$$

In which, $K_{L\times L}^{-1}$ is inverse of image covariance matrix and L is number of image bands. For pixel with CMFM value closer to unit, it means the pixel is more similar to the target.

2.2 Spatial Features in Target Detection

As it is mentioned above, spatial correlation of pixels contains some new information about target. It helps target detection to enhance its accuracy. In the other word, another solution to modify the accuracy of spectral target detection is to use spatial features as well as spectral features of each pixel together as input to general target detection algorithm.

Here, spatial correlation of each pixel to its neighbors is modeled by two methods including their mean and median. Therefore, for a hyperspectral image with n bands, there are n spectral features s_t as well as n spatial features m_t. For computation of spatial features m_t, a window should be defined around each pixel as neighborhood. We set 3*3 window and compute mean or median of eight neighbor values in each band as spatial features of that band. It means for pixel x_{ij} in band t, $s_t=x_{ij}(t)$ and m_t=mean or median $\{x_{i-1,j-1}(t), x_{i-1,j}(t), x_{i-1,j+1}(t), x_{i,j-1}(t), x_{i,j+1}(t), x_{i+1,j-1}(t), x_{i+1,j}(t), x_{i+1,j+1}(t)\}$.

2.3 Accuracy Evaluation Method

To compare the suggested spatial-spectral target detection method with conventional CMFM spectral target detection method, following steps are done. (a) True terrain map of the study area is generated manually through hyperspectral image by an expert image interpreter. In fact, true map is a binary mask that illustrates the target area clearly. (b) Target is detected in image through the target detection method. (c) Since the result of target detection is a soft similarity value between 0 and 1, it is converted to a hard value 0 or 1 by thresholding. Thresholding is done using ROC curves. ROC illustrates detection errors on check data based on concepts of detection power or positive and false alarm probabilities (Bradley, 1997). There are two curves of ROC which show target detection probability versus error detection probability and target detection probability versus threshold (Figure 1). The threshold is set by expert so that maximum target detection accuracy is derived.

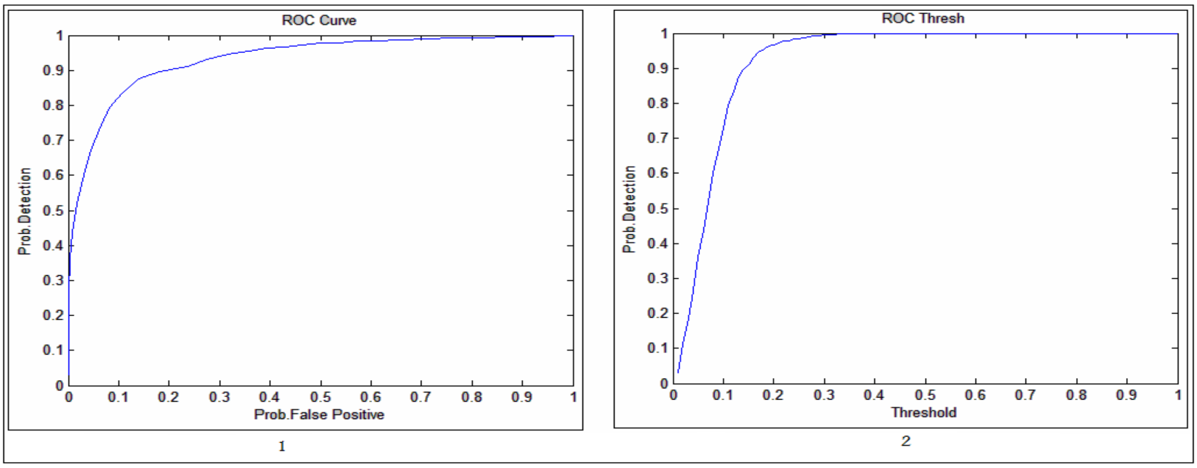

Figure 1: Curves (1) probability of detection versus probability of false alarm and (2) probability of detection versus threshold

(d) The result is compared to true map and confusion matrix is generated in which commission and omission errors for the target are represented. (e) Five criteria comprising of overall accuracy (OA), Kappa coefficient (K), producer's accuracy (PA), user's accuracy (UA), and noise are computed from confusion matrix (Rosenfield and Fitzpatric-Lins, 1986). In our study, K is used as accuracy evaluation factor, because OA is an optimistic criterion for accuracy evaluation but K is a realistic one.

3. EXPERIMENTS

This section first describes properties of experimental image data. Then, some practical tests and their quantitative and qualitative results are illustrated.

3.1 Experimental data

The above techniques are applied to CASI[2] hyperspectral images. CASI has a flexible spectral resolution capability. It means that the image data may have different numbers of bands, maximum 288. These numbers of bans cover a rang from 0.4 to 1.0 µm of electromagnetic spectrum, so the wide of each bands is about 10 µm. Spatial resolution of CASI is a function of its IFOV and altitude of airborne platform. It can vary from 1 to 10 meters. Dynamic rang of sensor is another parameter which produce the image data with 12 bits or 4096 gray levels. CASI, also is equipped by GPS and INS for In/Off fly rectification and georeferencing of images.

In our experiment, a CASI image taken from Toulouse urban area in south of France is with 32 bands and 2m pixel size is used. The target is building roofs covered with special material. Figure 2 shows the false color image from area with 128*128 pixels, true map and spectral signature of the target.

[2] Compact Airborne Spectrographic Imager

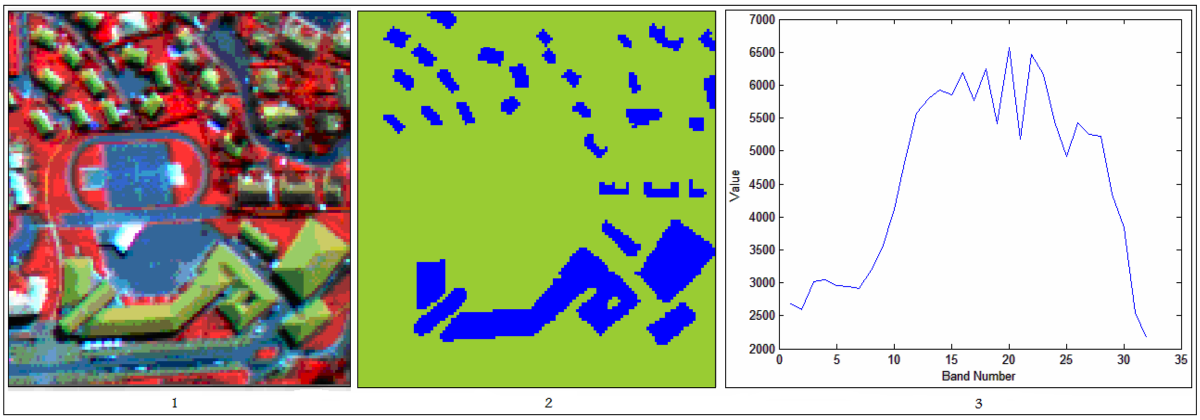

Figure 2: (1) the false color CASI image of study area (R=0.914, G=0.620, B=0.451), (2) Ground truth data for accuracy evaluation, (3) The extracted spectra of building material

The true map is generated by an expert using visual interpretation as well as checking spectral signature of selected pixel (Figure 2-2). The average of spectral signature of determined target pixels is used as spectral signature of target (Figure 2-3).

3.2 Result of Experiments

Figure 3 illustrates qualitative results of three target detection methods including CMFM with spectral features, CMFM with mean spatial-spectral features, and CMFM with median spatial-spectral features. Table 1 show the quantitative results derived from confusion matrix of above three methods.

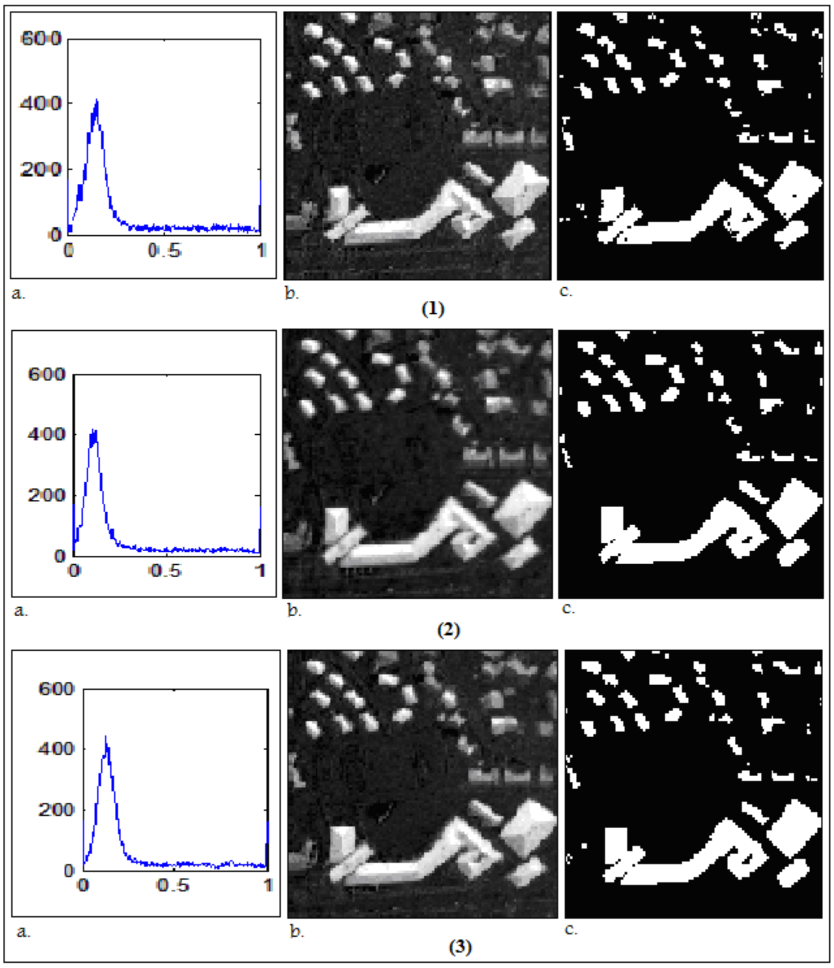

Figure 3: **(1)** result of CMFM without spatial features (2) CMFM with spatial mean features, (3) CMFM with spatial median features. In all cases, a, b, and c are image histogram, similarity value image and binary image after thresholding by ROC curves respectively.

Table 1: accuracy evaluation factors via confusion matrix

	K	OA	PA	UA	Noise
CMFM	**0.880**	0.968	0.883	0.908	0.032
CMFM+ Mean	**0.892**	0.971	0.908	0.910	0.029
CMFM+ Median	**0.887**	0.969	0.906	0.905	0.030

As you see in Table 1, adding spatial features to spectral target detection process leads to higher accuracy of detection. In the other word, it is possible to reduce 0.3% noise and enhance the detection Kappa coefficient from 0.880 to 0.892 that means about 1.2% accuracy improvement.

4. CONCLUSION

This research studied the effect of spatial correlation in spectral target detection result. The experiments demonstrated using spatial-spectral features in target detection can enhance the accuracy significantly in comparison of only spectral features. It is also seen that median features has better qualitative and quantitative results than mean features.

For future study, we recommend to model spatial correlation of image information in segment level instead of pixel level. It means textural features of image segments can be considered as spatial features.

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BIOGRAPHICAL NOTES

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