Korean Journal of Remote Sensing, Vol.22, No.1, 2006, pp.41~47

A Fast Algorithm for Target Detection in High Spatial Resolution Imagery

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Abstract : Detection and identification of targets from remotely sensed imagery are of great interest for civilian and military application. This paper presents an algorithm for target detection in high spatial resolution imagery based on the spectral and the dimensional characteristics of the reference target. In this algorithm, the spectral and the dimensional information of the reference target is extracted automatically from the sample image of the reference target. Then in the entire image, the candidate target pixels are extracted based on the spectral characteristics of the reference target. Finally, groups of candidate pixels which form isolated spatial objects of similar size to that of the reference target are extracted as detected targets. The experimental test results showed that even though the algorithm detected spatial objects which has different shape as targets if the spectral and the dimensional characteristics are similar to that of the reference target, it could detect 97.5% of the targets in the image. Using hyperspectral image and utilizing the shape information are expected to increase the performance of the proposed algorithm.

Key Words : Target Detection, Spectral Characteristics, Dimensional Characteristics.

1. Introduction

Recent high spatial resolution imagery offer a new quality of information about the Earth's surface, as even smaller objects, such as house plots, streets, and airplanes are recorded and displayed in greater detail. Because of the increasing information contents, algorithms for an effective automatic object extraction have been of great interest especially in the image intelligence area. Research toward the detection of man-made objects is typically based on aerial imagery and has been widely studied in photogrammetry and in the computer vision community for many years.

There have been two kinds of approaches for the detection of target objects in remotely sensed imagery. One approach is to detect subpixel targets in hyperspectral imagery. Because the detection of subpixel targets can be achieved only by exploiting spectral properties, most of researches have been focused on the spectral unmixing of the hyperspectral pixel (Manolakis *et al.*, 2001), the orthogonal subspace projection (Harsanyi and Chang, 1994), and the linearly constrained minimum variance (LCMV) beamforming method (Chang and Chiang, 2001). The other approach is to detect small objects in very

Received 2 January 2005; Accepted 3 February 2006.

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high spatial resolution panchromatic imagery by the shape classification of the unsupervised segmented result (Segl and Kaufmann, 2001), and by the template matching method (Thiang, 2001; Lee and Jeon, 2005).

The objective of this study is to find an effective algorithm for the detection of targets occupying multiple pixels in multispectral high spatial resolution imagery, especially in KOMPSAT2 imagery. Lee and Jeon (2005) reported that it is very difficult to implement template matching method to detect targets of arbitrary direction even though the shape information can be exploited at its maximum by template matching method. However, for the very small targets such as fighter planes and military vehicles, the shape of the targets is not preserved completely in the image due to the limitation of spatial resolution. Furthermore, the template matching method requires a lot of processing time because it should calculate correlation coefficient for every pixel in the image.

In this study, a fast algorithm for the target detection is proposed. The algorithm extracts the candidate pixels first which have the similar spectral characteristics to that of the reference target. Then groups of candidate pixels which form isolated spatial objects of similar size to that of the reference target are extracted as detected targets finally. The proposed algorithm was implemented as an executable software and experimented with test image which has 3 bands and the spatial resolution of about 1 meter.

2. Algorithm

1) Automatic Extraction of Reference Target

In this algorithm, the sample reference target pixels are extracted automatically. As shown in Fig. 1, the

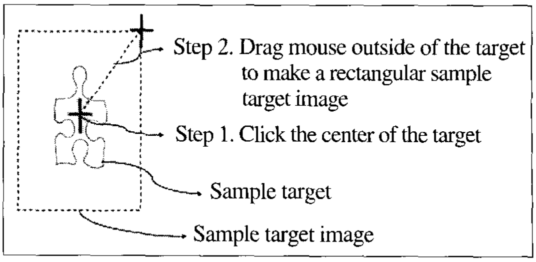


Fig. 1. Defining the sample reference target image using a mouse.

sample image should be defined by the image coordinate of the center point of the target and an image coordinate of a point outside of the target which forms a rectangular area large enough to include the whole target. The selected center point of the target became the center of the rectangular sample image. The reason why the rectangular area is defined by selecting the center point of the target and the other point instead of by selecting two coner points is to ensure the correct target to be extracted from the sample image.

Once the rectangular sample image is defined, it is classified in an unsupervised way. In order for this process to be done automatically, modified K-Means clustering algorithm is used (Kim, 2005). It is supposed that there are maximum of 4 classes in the sample image - target, shadow of the target, and other two classes for the background. After the unsupervised classification, it is very simple to extract the target class because the center point of the target had been already given when the rectangular sample image area was defined.

2) Characterization of Reference Target

The spectral and dimensional characteristics of the target to be detected are defined from the automatically extracted reference target. Let $S \subset Z^2$ be the set of reference target pixels. Let M_S be the spectral mean of S and let C_S be the covariance matrix of S. Then Mahalanobis distance from a pixel

X to M_S is defined as follows.

$$D_X = (X - M_S)^T C_S^{-1} (X - M_S) \tag{1}$$

Let D_{max} be the maximum distance for all sample target pixel $X \in S$.

$$D_{max} = max(D_X), X \in S \tag{2}$$

The maximum value of the Mahalanobis distances D_{max} will be used as a threshold value which decides whether a pixels is a candidate target pixel or not.

As dimensional characteristics of the target, the total number of sample target pixels N_P, and the maximum value of spatial dimension SD_{max} = max (SD_R, SD_X, SD_Y) and the minimum value of spatial dimension SD_{min} = min (SD_X, SD_Y) are defined as shown in Fig. 2. SD_X is the horizontal size of the extracted reference target, and SD_Y is the vertical size of the extracted reference target in pixel unit. SD_R is the radius of a circle which completely include the extracted reference target. Even in one image, the number of pixels occupied by the same kind of object at different location can not be exactly same due to the limitation of the spatial resolution and also due to the relative direction of the target to the scan line. Therefore, a dimension parameter P is introduced, which decide the possible spatial size of the object in the image. The value range of P is 0.0 ~ 1.0, and the target can occupy $N_P \pm N_P \times P$ pixels in an image.

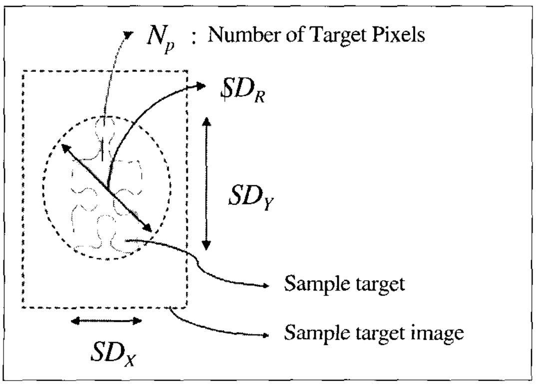


Fig. 2. Dimensional characteristics of the sample target.

Also the target can have spatial dimension range of $SD_{min} - SD_{min} \times P \sim SD_{max} + SD_{max} \times P$.

3) Extraction of Targets

The first step of target detection is to extract target candidate pixels from the input image based on the spectral characteristics of the reference target. For a given pixel X, Mahalanobis distance D_X to M_S, the spectral mean of sample target pixels, is calculated. If D_X to M_S is less than D_{max}, the given pixel X is extracted as a target candidate pixel. Once all the target candidate pixels are extracted, the spatial relation of those candidate pixels is analysed. Then each isolated groups of candidate pixels which are spatially connected are treated as spatial objects (Kim, 2005). For each objects, the number of pixels and the spatial dimensions are calculated. If these dimensional values of an object are in the range of the reference target's dimensional characteristics, the object is finally detected as a target.

3. Experiments and Discussion

The proposed algorithm was implemented as an executable software which has a graphic user interface using C++. Fig. 3 shows the test input image for the experiments. The spatial resolution of the image is about 1 meter and the image has 3 spectral bands. There are total of 41 fighter planes in the image.

Fig 4a shows one of the fighter planes in the input image. The fighter plane in Fig. 4a is used as a reference target for the detection of other fighter planes in the entire image. Fig. 4b shows the process of defining the rectangular sample image area using a mouse. Fig. 4c shows the unsupervised classification results. The black pixels in Fig. 4d shows the finally extracted sample target.

Fig. 5a shows the extracted target candidate pixels

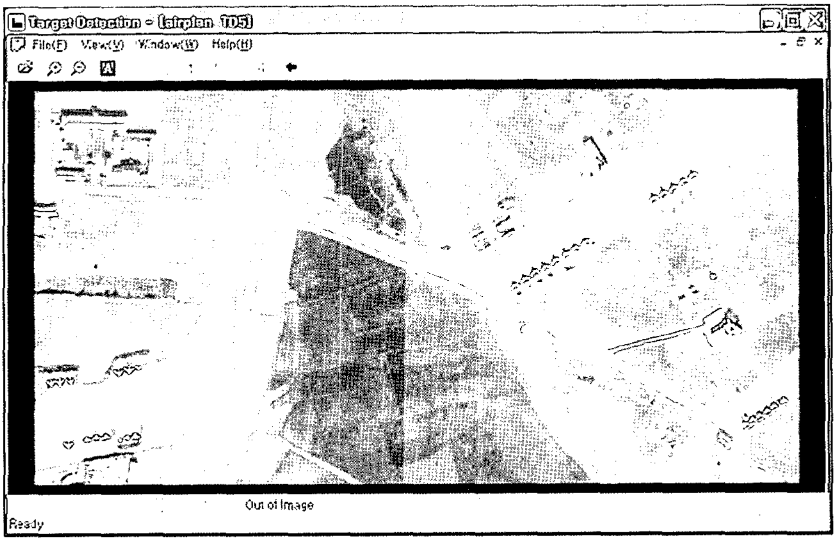
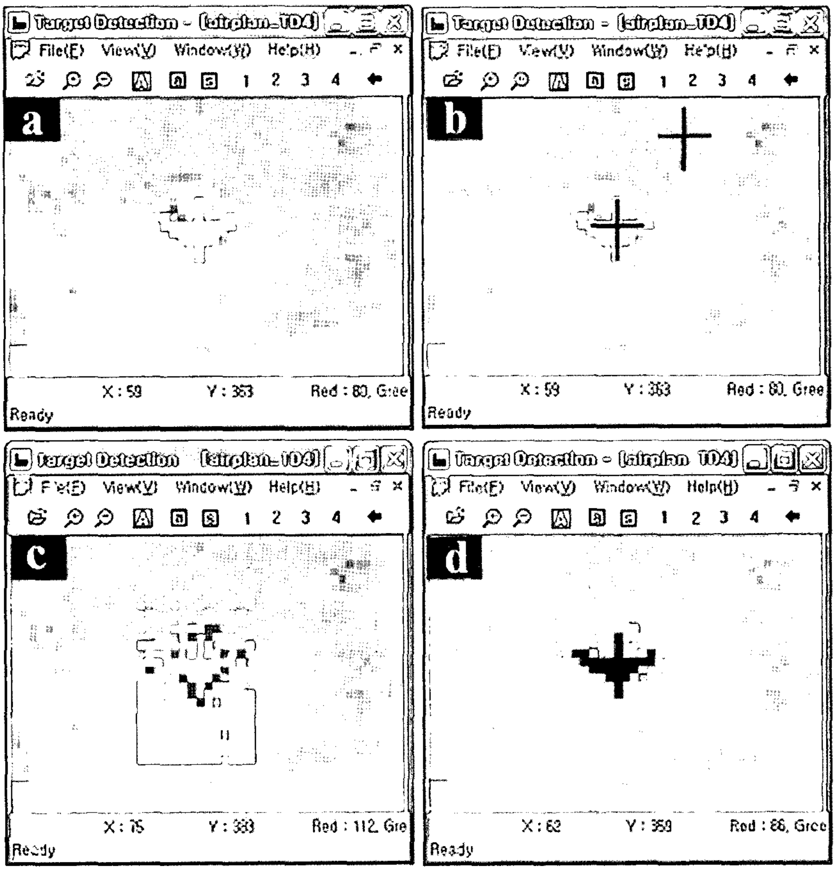


Fig. 3. Test image for the experiments. There are a total of 41 fighter planes.



Figs. 4. (a) Image of a fighter plane. This plane is used as a reference target. (b) Process of defining the sample image. (c) Unsupervised classified result. (d) Extracted target (black pixels).

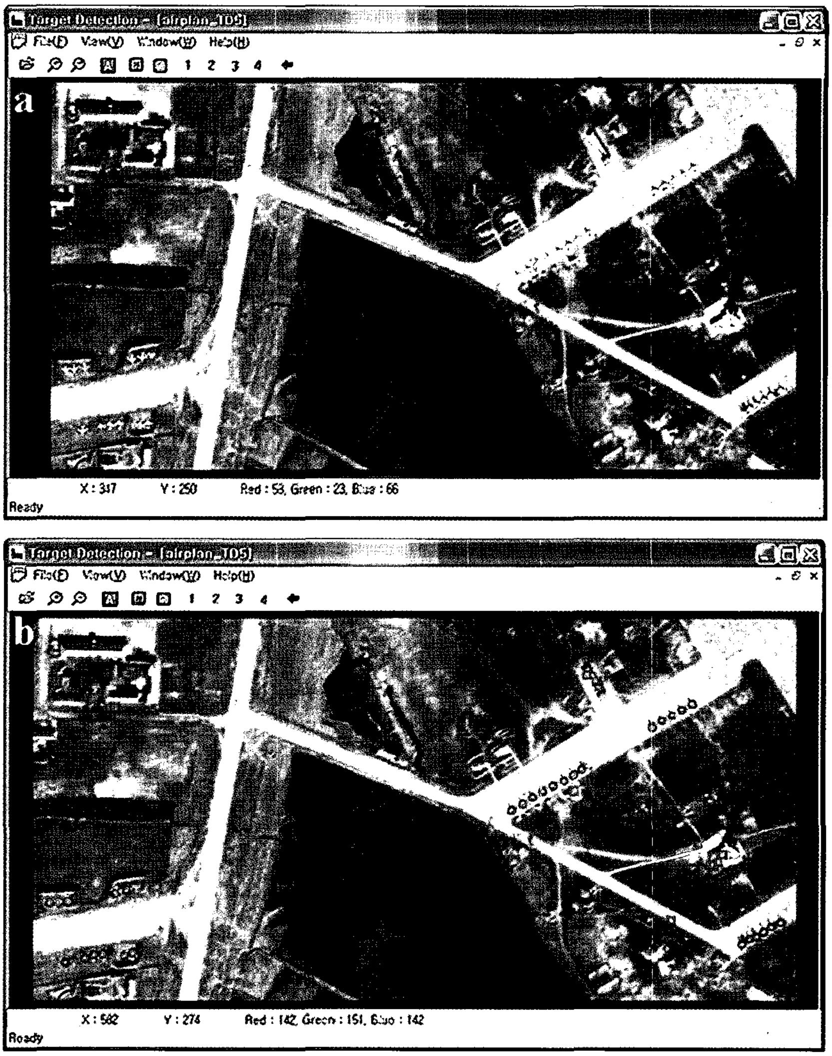


Fig. 5. (a) The result of target candidate pixel extraction (yellow pixels). (b) The target detection results using the dimension parameter value of 0.8. Total of 50 targets are detected as fighter planes. Among them, 40 targets are true fighter planes and the other 10 targets are buildings and road. About 97.5% of the fighter planes in the image was detected as targets. The red circle means the correctly detected fighter planes and the blue rectangle means misidentified detection - buildings and road.

(yellow pixels) in the entire image. Not only the fighter planes but also some road and buildings are extracted as target candidates due to their spectral similarity to that of the sample target. Fig 5b shows the finally detected targets with the dimension parameter value of 0.8. Total of 50 targets are detected as fighter planes. Among them, 40 targets are fighter planes and the other 10 targets are buildings and road. The red circle means the correctly detected fighter planes and the blue rectangle means misidentified detection - buildings and road. It can be also noticed from Fig. 5 that targets with arbitrary direction are detected because the shape information is not used at all in this algorithm.

Table 1. Target detection results with the dimension parameter range of 0.3 ~ 0.8.

Dimension Parameter	Detected Results		Accuracy	Misidentification	Target Detect Ratio
	Planes	Non Planes	Planes/Detected Targets	Non Planes/Detected Target	Detected Planes/Planes in Image
0.3	27	1	27/28 (96.5%)	1/27 (3.7%)	27/41 (65.8%)
0.4	32	3	32/35 (91.4%)	3/35 (8.5%)	32/41 (78.0%)
0.5	35	4	35/39 (89.7%)	4/39 (10.2%)	35/41 (85.3%)
0.6	35	6	35/41 (85.3%)	6/41 (14.6%)	35/41 (85.3%)
0.7	38	7	38/45 (84.4%)	7/45 (15.5%)	38/41 (92.6%)
0.8	40	10	40/50 (80.0%)	10/50 (20.0%)	40/41 (97.5%)

Table 1 shows the target detection results with the dimension parameter range of 0.3 ~ 0.8. When the value of 0.8 is used as the dimension parameter, 97.5% of the fighter planes in the entire image are detected as targets. However, also total of 10 non fighter planes (buildings and road) are detected as targets. On the contrary, when the dimension parameter is 0.3, there is just 1 misidentification but only 65.8% of the fighter planes in the image are detected as targets.

Fig. 6a shows a fighter plane which could not be detected at all due to its size. It seems to be a different kind of plane from the plane used as a sample target. The fighter planes in Fig. 6b also seems to be different from the planes in Fig. 6a but all of them are extracted as targets when the dimension parameter value of 0.8 is used. However, because those two planes indicated by white arrow in Fig. 6b are located too close, they are not detected as targets at all when the dimension parameter is less than 0.8.

4. Conclusion

A fast algorithm for target detection in high spatial resolution imagery based on the spectral and the dimensional characteristics of the target was proposed. The proposed algorithm was implemented as an executable software and tested using 1 meter spatial resolution, 3 band image. Maximum of 97.5% of the targets in the image could be detected with the misidentification ratio of 20.0%. When a very strict target size criteria was applied, 65.8% of the targets in the image could be detected but the misidentification

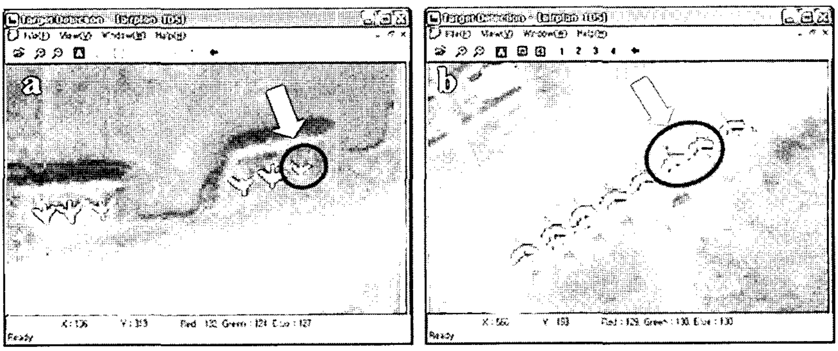


Fig. 6. (a) The fighter plane which can not be detected at all due to its size. It seems to be a different kind of plane from the fighter plane used as a sample target. (b) Because those two planes indicated by white arrow are located too close, they are not detected as targets when the dimension parameter is less than 0.8.

ratio was only 3.7%. Considering that there were at least three different kinds of fighter planes in the input image which have different size and shape and also that in this study only one kind of fighter plane was used as a sample target, it is expected that more applicability test to various kinds of imagery and targets would enhance the performance of the algorithm. It is also expected that using hyperspectral image and utilizing the shape information would increase the performance of the proposed algorithm dramatically.

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