Combining CFAR with anomaly detection at hyperspectral images

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ABSTRACT

Over the last few years, we have developed an algorithm which detects anomalous targets in hyperspectral images. The algorithm takes a hyperspectral cube with a completely unknown background, segments the cube, assigns the largest clusters as background, and determines which pixels are anomalous to the background. In the work to be presented here, we will add two additional modules. First, since our present mission is to detect military targets in a fairly barren rural background, we use the SAVI (or NDVI) metric to detect items which appear to contain chlorophyll. In this way, we can eliminate objects which in retrospect were the right sizes and shapes but were in reality plants. Second, we have developed CFAR methods to achieve a Constant False Alarm Rate while giving us the maximum probability of detecting the targets. Actual data will be analyzed by the algorithm; the ability to both determine if a target is present and where its location is will be shown.

KEY WORDS: Anomaly Detection, SRC, Multispectral Data, Hyperspectral Data, CFAR, NDVI, SAVI.

1. INTRODUCTION

Multi-spectral and hyperspectral images are images which contain spectral information for each of the measured pixels; in general, such measurements are taken in the visible and near infrared regimes. Over the last few years, we have developed an algorithm (Silverman-Rotman-Caefer (SRC)) for the detection of pixels which are anomalous in that they don’t fit into the background. This algorithm in general has three parts: (a) Segmentation of the background into clusters and the determination of which clusters are part of the background, (b) determination of the spectral distance of each pixel from the background and (c) morphological processing to determine which pixels are part of an object possible representing the target. While the algorithm in general works well \textsuperscript{[1]-[4]}, it can be improved if we have some a-priori knowledge of the nature of the target and of the background. In particular, if we know that plant growth may be present in the image but that it is definitely not related to the target, we can use some of the well-known algorithms to detect chlorophyll and eliminate such pixels from potential targets. This will be most relevant when the vegetation sparse and could have been identified as a potential target.

Our paper is thus arranged as follows: Section 2 represents a summary of the original segmentation and anomaly detection algorithm. Section 3 details the possible indexes that can be used for detecting plant life. Sections 4 and 5 briefly present our method for combining these algorithms and present the results we obtain, respectively. The paper concludes with conclusions and possible future work in Section 6.

2. ANOMALY DETECTION: THE SRC ALGORITHM

The SRC algorithm \textsuperscript{[1]-[4]} for the detection of anomalous objects as described as follows:

1. Produce a two-dimensional histogram where the values of each axis are determined by each of the first two principal components analyzes (PCA) images (based on the original cube).

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2. Find the peaks in this image and then associate each of the possible combinations of principal component values to one of these peaks. At this point, the original cube is segmented. Note that this algorithm has no particular minimum size of the existing clusters.
3. Define the largest segments to be background; choose enough segments so that roughly 95% of the area is covered (minimum value).
4. Each cluster that contributed is averaged separately over its constituent pixel members; the resulting endmembers are defined to be the endmembers of the background.
5. Every pixel in the original dataset is now reevaluated by its minimum angular distance, by using SAM (Spectral Angle Mapper, Eq. 1) to any of these endmembers.

\[
SAM: \quad \alpha = \cos^{-1}(x, y) = \frac{x^T y}{||x|| \cdot ||y||}
\]

(1)
6. An analog morphological operation \(^3\) is next performed to eliminate objects which are either too small or too large to fit the target criteria.
7. The results are analyzed by producing ROC (Receiver Operating Characteristics) curves relating the number of false alarms to the number of targets detected.

3. PLANT INDICES

3.1. Normalized Difference Vegetation Index (NDVI)
This metric evaluates the degree of photosynthesis going on in potential plant life \(^5\), \(^6\). The healthier the plant or the more closely packed the plants are, the higher the index (between +1 to -1). The index is calculated by comparing the reflectance in the NIR (near infrared) and the Red band. The use of the index can be done only after the correction of the data for the atmospheric absorption. The value is:

\[
NDVI = (NIR - RED) / (NIR + RED)
\]

(2)

3.2. Soil-Adjusted Vegetation Index (SAVI)
The SAVI metric is similar to NDVI in that it again uses the difference of the brightness of the individual pixels in the infrared and the red wavelengths \(^7\). The algorithm contains an additional factor \(L\) which is used to characterize the type of bare ground present in the image. The metric is given by:

\[
SAVI = [(NIR - RED) / (NIR + RED + L)] \ast (1 + L)
\]

(3)
where \(L\) varies between 0 to 1; if the type of background is not known, \(L\) is set to 0.5.

4. COMBINING THE ALGORITHMS
In our anomaly detection algorithm in step 4, we calculated average signatures which define the background. If the plant life is sparse in the image, we are very likely not to include such a signature into the background; thus such pixels will be determined to be potential targets. To be able to counter such a possibility, we will deliberate seek out the pixels with the highest values of NDVI or SAVI. These pixels will be averaged together to form a new endmember which will be added to the background endmembers. Thus, other pixels which are anomalous but are based on plant-like signatures will be eliminated from consideration as targets.

4.1. Constant False Alarm Rate (CFAR)
The CFAR module allows us to determine if a target is present by examining a final output image which (hopefully) contains all the information derived from the original image \(^8\). The CFAR algorithm has as input the minimum angular distance image from the SRC algorithm; it calculates the threshold and gives us as output a binary image, where black is the non target area and white are pixels stronger than the threshold. To achieve a threshold based on a CFAR, the steps are as follows:
1. On the histogram of the two-dimensional minimum angular distance, cut the upper and lower 1% of the pixels.
2. Find the average ($a$) and the standard deviation ($\sigma$) for the main 98% of the pixels. By assuming a Gaussian distribution for this part, define a desirable false alarm rate $P$ and use Eq. 4 to find the required threshold ($x$):

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{-(x-a)^2}{2\sigma^2}\right]$$

(4)

3. Use the threshold on the minimum angular distance and find which pixels are stronger than that threshold.

5. SIMULATED EXPERIMENT

To understand the results, we use ROC curves derived in the following way: We count the total number of pixels on targets (from the ground-truth), giving the total number of target pixels ($N_t$). For each anomaly image at a given threshold, we determine a point on the ROC curve by using Eq. 5 and 6:

$$P_{td} = \frac{N_{\text{panel}}}{N_t}$$

(5)

$$P_{fa} = \frac{N_{\text{non-panel}}}{N_{\text{scene}}}$$

(6)

where the numerators are the number of panel (targets) and non-panel pixels above threshold and $N_{\text{scene}}$ is the total number of pixels in the scene that are not part of the targets. For comparing results from several cases, we can use the interval area [9]. To do so, we need to find the area from 0 to our maximum $P_{fa}$ for each case.

5.1. Real Data Cube (Field Test Data)

We tested the algorithm on real multispectral data, from the sensor IKONOS, with 4 bands: Blue (0.45 - 0.53 $\mu$m), Green (0.52 - 0.61 $\mu$m), Red (0.64 - 0.72 $\mu$m) and Near Infra-Red (0.77 - 0.88 $\mu$m), with dimensions of 180 by 110 pixels, showing a desert region in Israel (Figure 1.a is the RGB image). In the image, there is an anomalous high voltage pole in the upper half of the image on the left; this is sparse vegetation present in the image. Figure 1.b is the blown up projection of this area from the RGB image and Fig. 1.c is the ground truth for the high voltage pole.

5.2. Experimental results

Each band of the original image can be seen in Fig 2.a-d, and the principal component images can be seen in Fig. 3.a-d. The resulting classification shows that most of the pixels fall in two classes (Fig.4.a). The background can be seen in Fig. 4.b (black color). The resulting anomaly distance image, using the spectral angle metric, is seen in Fig. 5.a. Fig. 5.b show the pixels that pass the threshold calculated base on the CFAR technique. As can be seen, the high voltage pole stands out as anomalous along with a patch of vegetation nearby. If we calculate the SAVI metric (with L=1), we get the image shown in Fig. 6.a, and if we calculate the NDVI metric, we get the image shown in Fig. 6.b. If we take the 0.5% highest pixels of the SAVI index and add their average signature to the group of vectors representing the background, a new anomalous pixel image is produced (Fig. 7.a). Fig. 7.b is the anomaly distance after threshold. These results are based on the three average background vectors (Fig. 8.a-b): two vectors are calculated from the original background and one is calculate from the highest pixels (0.5%) from the SAVI histogram.

5.3. Comparing of the Results

As can be seen by eye, there is a strong correspondence between the ground-truth and the upgrade result (Fig. 7.b). Fig. 9 is a ROC curve for the two cases: the basic SRC algorithm and the SRC combined with SAVI. We can see that if we focuses on the blown up area of the curve ($P_{fa}= [0 : 0.1]$) we can see that the improvement is significant: the area increases by 9.4%. This implies that more true targets are detected for the same false alarm rate.

6. CONCLUSIONS

Anomalous pixel detection for target acquisition can be improved by our knowledge of the characteristics of the multi-spectral cube being analyzed. The initial anomaly detection algorithm was constructed with the assumption that nothing
was known about the background. Since we are dealing not just with a theoretical academic exercise but with a sincere desire to find genuine targets, we have considered adding the knowledge that the target is not plant-like in its spectral response. As we have shown, improved results from our algorithm are obtainable with such an assumption.

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REFERENCES


FIGURES

a. The RGB scene

b. Zoom at the high voltage pole

c. Ground truth

Fig.1: Original image
Fig. 2: The bands of the original image

Fig. 3: The bands of the principal components analyzes

Fig. 4: Classification

Fig. 5: Minimum angular distance

Fig. 6: Plant indices of the original image

Fig. 7: Minimum angular distance (combine with SAVI)
a. Average signatures of the original background classes

b. Average signature of the top 0.5% of SAVI

Fig.8: Signatures

Fig.9: ROC: Minimum angular distance of SRC and SRC combine with SAVI