Signal Processing 124 (2016) 115–131

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

A spectral-spatial based local summation anomaly detection method for hyperspectral images ☆

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ARTICLE INFO

Article history:
Received 23 June 2015
Received in revised form
5 September 2015
Accepted 29 September 2015
Available online 17 October 2015

Keywords:
Hyperspectral imagery
Anomaly detection
Spectral-spatial integration
Local summation strategy

ABSTRACT

Anomaly detection is one of the most popular applications in hyperspectral remote sensing image analysis. Anomaly detection technique does not require any prior features or information of targets of interest and has draw the increasing interest in target detection domain for hyperspectral imagery (HSI) in the recent twenty years. From hyperspectral data, the approximately continuous spectral features which are attributed to the high spectral resolution of hyperspectral image can be achieved. Unfortunately, most conventional anomaly detectors merely take advantage of the spectral information in hyperspectral data and rarely give the consideration to spatial information within neighboring pixels. With the development of remote sensing technology, the high spatial resolution can also be acquired by the hyperspectral airborne/spaceborne sensors. Then, further improvement in algorithmic performance may be achieved if both the spectral and spatial information is combined. This article proposes a novel local summation anomaly detection method (LSAD) which combines the multiple local distributions from neighboring local windows surrounding the pixel under test (PUT) with spectral-spatial feature integration. Some other detection performance enhanced operations such as feature extraction and edge expansion are also used. The proposed local summation anomaly detection method makes allowance for exploiting more sufficient local spatial neighboring relationship of local background distribution around the test pixel considered in detection processing. Moreover, summated local background statistics can get better performance in suppressing background materials and extruding anomalies. Feature extraction enables LSAD with robust background feature statistics and edge expansion can ensure no loss of edge detection information. Experiments are implemented on a simulated PHI data and two real hyperspectral images. The experimental results demonstrate that the proposed anomaly detection strategy outperforms the other traditional anomaly detection methods.

1. Introduction

Recent years have witnessed the quick development of image processing theory [1–8]. One newly developed imaging technique, IMAGING SPECTROSCOPY, which is also known as hyperspectral imaging, draws great interests of researchers in image processing field [9–11]. It is a type of remote sensing imaging technology concerned with the extraction of information about objects lying on the Earth ground surface, based on radiant signal acquired

☆ This work was supported in part by the National Basic Research Program of China (973 Program) under Grants 2011CB707105 and 2012CB719905, the National Natural Science Foundation of China under Grants 61471274 and 41431175, the Natural Science Foundation of Hubei Province, China under Grants 2014CFB193 and the Fundamental Research Funds for the Central Universities under 211-274175.
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http://dx.doi.org/10.1016/j.sigpro.2015.09.037
0165-1684/

by spaceborne or airborne sensors [9,10]. Hyperspectral imaging sensors are passive sensors that simultaneously attain images with hundreds of continuous and narrow regions of the electromagnetic spectrums [11]. Approximately continuous spectral characteristics of ground surface materials can be achieved from hyperspectral image because of its high spectral resolution which is usually less than 10 nm [12–15]. This is the most different trait of hyperspectral images, compared with the traditional panchromatic and multispectral remote sensing images [16]. Then a hyperspectral image “cube” can be established by combining two spatial dimensions (width and height) and a spectral dimension together [17]. By means of approximately continuous spectral curves of ground surface materials, adequate spectral information can be provided for hyperspectral applications such as classification, target detection etc. [18]. For current hyperspectral practical application domains, spectral information is an important essential factor which is still mainly under consideration. Thus, significant attention in the field of hyperspectral remote sensing research is devoted to develop algorithmic techniques to detect, classify, identify, quantify, and characterize objects and features of interest in the captured data [19].

Two types of target detection techniques are usually interested in target detection domain: known and unknown with target spectra. If target spectra are known in the processing of target detectors, it is also named spectral matching detection algorithms refer detectors that require the spectral information about the targets of interest, and they try to identify pixels whose spectrum exhibits a high degree of correlation to the expected signature [20]. However, in most cases it is difficult to obtain the spectrum of ground surface objects in hyperspectral images. The absorption and scattering of the atmosphere, the subtle effects of illumination and the spectral response of the sensor must all be considered in measuring the spectral properties of a material through the atmosphere [21]. Moreover, spectral variability also needs to be addressed in this kind of target detection [22].

The multiplicity of possible spectra associated with the objects of interest and the complications of atmospheric compensation have led to the development and application of target detection without target spectra which is called anomaly detection. Anomaly detection algorithms are more practical in actual applications. Anomaly detection technique which does not require any prior features or information of targets of interest has been of great interest in hyperspectral imagery processing in recent twenty years [23–26]. Hyperspectral anomaly detection technique has been successfully applied in many application domains such as mineral reconnaissance, border monitoring, search-and-rescue etc. in recent years [27].The goal of anomaly detection is to detect a small quantity of pixels in the hyperspectral image whose spectral characteristics differ significantly from those of a large proportion of pixels in the hyperspectral data cube, and then the hyperspectral image is segmented into two parts: anomaly targets and backgrounds [28]. Anomaly targets are usually inclined to be small man-made objects of minor quantity of pixels whose spectra are distinctly different with other major pixels in the images. For example, for those entrusted with search-and-rescue missions anomalies may be downed-aircraft or adventures lost in the wilderness. With national defense, anomalies may be tanks, aircraft, surface-to-air missile launchers, command bunkers, and other objects of military significance scattered across a battlefield. And for civilian applications, anomalies may be vehicles located in an urban or natural field.

Anomaly detection methods mainly extract the knowledge from backgrounds and use the differences between anomaly targets and the backgrounds to detect the anomalies [29]. According to the different ways of making use of information in hyperspectral images, anomaly detection methods are mainly classified into two kinds: spectral information based and spectral-spatial based. Some conventional anomaly detectors think hyperspectral image as a whole sample dataset and extract the background statistical features from it. These detectors can be called global anomaly detectors [30]. Global anomaly detection algorithms only utilize the spectral information in hyperspectral images. However, the global anomaly detector will not find an isolated local target whose signature is similar to that of global background material [31]. For example, consider a scene containing the isolated trees on a grass plain. Each separate tree may be seen as a local spectral anomaly even if the image contains a separate region with many pixels of trees. The global spectral anomaly detection algorithms are susceptible to this type of clutter and would generate false alarms. Moreover, although the spectral feature vector contains a lot of information about the spectral properties of the pixels, the spectral-vector-based HSI analysis just process each pixel independently, without considering the spatial relationship of neighboring pixels [32].

Most traditionally common used detectors or classifiers are mainly using the spectral information in the “hypercube”. They only deal with a set of first-order data as input, i.e., the vector representation, which is commonly used to represent the spectral feature of a certain pixel in HIS [33–35]. With the development of airborne/spaceborne remote sensing technology, spatial resolution of hyperspectral image increased gradually. Airborne/spaceborne hyperspectral sensors such as Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) [36] and Hyperspectral Digital Imagery Collection Experiment (HYDICE) [37] can reach a spatial resolution of 1–10 m. This level of spatial resolution can make ground surface materials in hyperspectral images contain a wealth of spatial information. And then if the spatial information is joined into hyperspectral applications, better performance can be potentially achieved. Some research on spectral-spatial integration has been implemented in hyperspectral image processing algorithms. Endmember extraction methods such as Abundance-Constrained Endmember Extraction (ACEE) [38] and Automatic Morphological Endmember Extraction (AMEE) [39] algorithms join spectral and spatial information and obtain improved performance than conventional methods. Some researchers also use spectral information as well as spatial information to achieve further improvement in classification [40,41]. Anomaly detection algorithms mainly utilize two ways to integrate spectral and spatial information: model based methods and window filtering. Anomaly detectors such as Gaussian Markov Random Field (GMRFAD)