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Vehicle detection in remote sensing imagery based on salient information and local shape feature☆

Xinran Yu [a], Zhenwei Shi [a,b,c,*]

[a] Image Processing Center, School of Astronautics, Beihang University, Beijing 100191, PR China
[b] State Key Laboratory of Virtual Reality Technology and Systems, Beihang University, Beijing 100191, PR China
[c] Beijing Key Laboratory of Digital Media, Beihang University, Beijing 100191, PR China

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ABSTRACT

Vehicle detection in high resolution optical imagery, with a variety of civil and military applications, has been widely studied. It is not an easy task since high resolution makes optical imagery complicated, which usually necessitates some rapid predetection methods followed by more accurate processes to accelerate the whole approach and to decrease false alarms. Given this "coarse to fine" strategy, we employ a new method to detect vehicles in remote sensing imagery. First, we convert the original panchromatic image into a "fake" hyperspectral form via a simple transformation, and predetect vehicles using a hyperspectral algorithm. Simple as it is, this transformation captures the salient information of vehicles, enhancing the separation between vehicle and clutter. Then to validate real vehicles from the predetected vehicle candidates, hypotheses for vehicles are generated using AdaBoost algorithm, with Haar-like feature serving as the local feature descriptor. This approach is tested on real optical panchromatic images as well as the simulated images extracted from hyperspectral images. The experiments indicate that the predetecting method is better than some existing methods such as principal component analysis based algorithm, Bayesian algorithm, etc. The whole process of our approach also performs well on the two types of data.

1. Introduction

Vehicle detection is of great significance because of its wide applications such as transportation control, road verification, visual surveillance, etc. With the development of sensor technology, high resolution optical images such as GeoEye, QuickBird, Google-Earth are publicly available and become one of the data sources which have been most studied. High resolution images produce more details of vehicles, so the local shape and contextual information are widely used to generate hypotheses separating vehicles from non-vehicle objects. However, higher resolution also makes optical imagery more complicated, which increases the difficulty in detecting vehicles.

In the past two decades, many different approaches have been investigated. These approaches can be roughly divided into two categories: statistics based methods and feature based methods. For the former ones, algorithms such as principal component analysis, Bayesian model as well as threshold segment methods [12] are usually used. As to the latter ones, great attention has been paid to the different kinds of features such as histogram of oriented gradients, local binary patterns, Haar-like features, etc. [5]. But in most cases, the existing approaches combine different methods together so as to detect vehicles more efficiently. For example, Leitloff et al. [7] come up with a sophisticated model of typical traffic situations in urban areas. Firstly, vehicle queues are detected using a line extraction technique, then adaptive boosting algorithm in combination with Haar-like features is employed to separate vehicles out of non-vehicles. Eikvil et al. [3] employ an automatic approach consisting of a segmentation step followed by two stages of classification to detect vehicles on highways and inner city roads. Choi and Yang [2] utilize Mean-shift algorithm to extract car blobs first and detect cars using log-polar shape descriptor. Cao et al. [1] extract the boosted Histogram Orientation Gradients features, followed by a support vector machine to find out vehicles. Kembhavi et al. [6]

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* Corresponding author at: Image Processing Center, School of Astronautics, Beihang University, Beijing 100191, PR China. Tel.: +86 10 823 39 520; fax: +86 10 823 38 798.
E-mail address: shizhenwei@buaa.edu.cn (Z. Shi).

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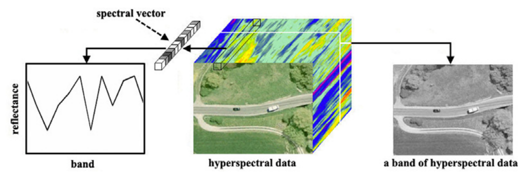

Fig. 1. The middle is a hyperspectral image, the left part is the spectral vector of a pixel, and the right part is a single band which is similar to optical image.

propose a vehicle detector including partial least squares algorithm and a very large set of image descriptors, including color statistics, histograms of oriented gradients as well as a descriptor that captures the structural characteristics of objects.

In this paper, we want to further investigate the problem of vehicle detection in panchromatic remote sensing imagery. Our approach involves a transformation from panchromatic image to a "fake" hyperspectral form. So hyperspectral imagery is introduced briefly here. Hyperspectral image is an image consisting of a set of bands, as Fig. 1 shows. In Fig. 1, each pixel in the hyperspectral image corresponds to a vector named as "spectrum", rather than a single value. The left part of Fig. 1 shows the spectrum of a pixel, which will be denoted as "spectral vector" in the rest of this paper. Some bands in a hyperspectral image may visually be similar to optical image, but others may not. The right part of Fig. 1 shows a certain band. In hyperspectral data, spectral vectors can characterize different kinds of materials since the spectral vectors of different materials usually have different patterns.

Since both spectral vectors of hyperspectral image and the gray values of optical panchromatic image contain discriminative information of different objects, we believe that there could be some underlying relationships between the two types of data. Motivated by this idea, for vehicles in optical panchromatic images, we propose a vehicle detector (or vehicle candidates detector) which detects vehicle candidates in a hyperspectral manner. We first convert the panchromatic image into a "fake" hyperspectral form by transforming neighbored pixels in a panchromatic image into spectral vectors. Then we employ a hyperspectral algorithm to extract vehicles candidates using the salient information. Finally, to validate real vehicles from vehicle candidates, hypotheses for vehicles are generated using AdaBoost classifier, with Haar-like feature serving as the local feature descriptor. Fig. 2 presents the outline of our method.

The rest of this paper is organized as follows. Section 2 describes the extraction of vehicle candidates, including the transformation from panchromatic image to "fake" hyperspectral image and the hyperspectral algorithm "Reed-Xiaoli" (RX) [11]. Section 3 briefly depicts the process of Haar-like feature extraction as well as AdaBoost classifier. Section 4 presents the experimental results on real and simulated data. Finally, Section 5 provides the discussion and conclusion of this paper.

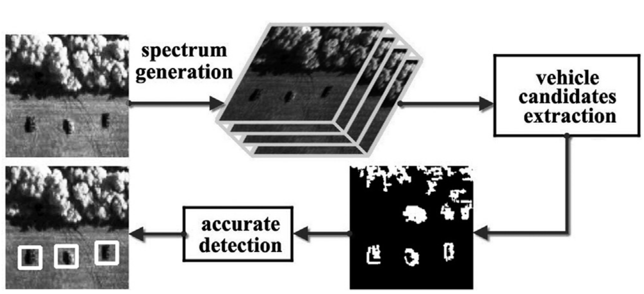

Fig. 2. The outline of our method, which can mainly be separated into two parts: vehicle candidates extraction and accurate detection.

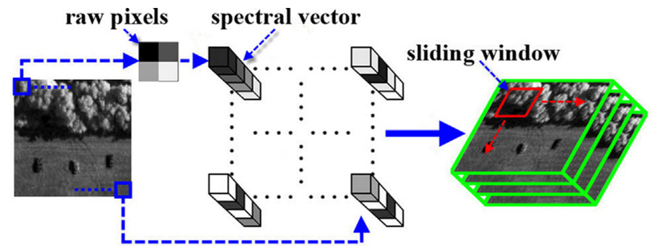

Fig. 3. The process of spectral vector generation. The left one is the original image, the right one is the produced hyperspectral form of data with 4-dimensional spectral vectors. The window is the sliding window. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

2. Vehicle candidates extraction

With the purpose of detecting vehicle candidates preliminarily and quickly, a rapid method to extract all vehicle candidates from the whole image without any omission is needed.

The vehicles in an image are usually more salient than background because the neighbored pixels of vehicles are variable while those of background have great similarities. Then, if we convert the panchromatic imagery into a hyperspectral form, by transforming the neighbored pixels into spectral vectors (defined in Section 1), the spectral vectors of vehicles will be very distinct from those of background. Since vehicle pixels usually make up only a small proportion in a whole image, this distinction can be regarded as a kind of anomaly. "Reed-Xiaoli" (RX) algorithm [11], an unsupervised hyperspectral method, can find out the spectral vectors with anomalies and the spectral vectors detected by RX are the vehicle candidates to be further analyzed.

The data produced through the transformation process can be viewed as a kind of "fake" hyperspectral image, i.e., the produced data only has the hyperspectral form but not the hyperspectral information. However, this "fake" hyperspectral imagery can represent data more properly in terms of RX algorithm, which facilitates the subsequent process and analysis. More importantly, through this transformation, the univariate gray level distribution of an one-band image is converted into a multivariate one, enhancing the separability between vehicle and non-vehicle object.

2.1. Spectral vector generation

We now explain in details the transformation from a panchromatic image to a "fake" hyperspectral image.

Given an $H \times W$ panchromatic image, a $k \times k$ window is first masked on it and the pixels within the window are copied and shifted into a k^2-dimensional vector, serving as the produced spectral vector. Then the $k \times k$ window traverses throughout the whole image from left to right, from up to bottom and a three-dimensional $H \times W \times k^2$ data cube (ignore the boundary pixels) is finally obtained, as shown in Fig. 3. Note that the $k \times k$ window is the blue square in the left part of Fig. 3 rather than the red sliding window on the right. The red sliding window will be explained later.

2.2. RX algorithm

After generating the "fake" hyperspectral image, the hyperspectral algorithm, "Reed-Xiaoli" (RX), will be explained as we now present. In a produced hyperspectral image, the spectral vector of each pixel can be denoted as a P-dimensional vector of the form $\boldsymbol{x} = (x_1, x_2, \ldots, x_P)^T$ where $x_i (i = 1, 2, \ldots, P)$ denotes the value in each band. Then a hyperspectral image with N pixels in total can be denoted as a $P \times N$ matrix $\boldsymbol{X} = [\,\boldsymbol{x}(1), \boldsymbol{x}(2), \ldots, \boldsymbol{x}(N)]$ in which each column denotes the spectral vector of each pixel. RX algorithm