Building detection using hyperspectral Images by Support Vector Machines

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Abstract

Building detection is one of the important applications in processing hyperspectral images. In order to detect complete and precise building information from hyperspectral data, advanced data analysis methods are required. Algorithms based on spectral-identification are sensitive to spectral variability and noise in acquisition. In most cases, the spatial distributions and spectral signature are unknown, so each pixel is separately examined and if it significantly differs from the background, it is regarded as an object. On the other hand, there are many classic (e.g. Maximum Likelihood (ML)) and non-classic (e.g. Modified Spectral Angle Similarity (MSAS) as a Deterministic and Adaptive Coherence Estimator (ACE), Covariance-based Matched Filter Measure (CMFM) as sub-pixel approach) algorithms for building detection.

In this study, first we propose a theoretical discussion aimed at understanding and assessing the potentialities of MLC, MSAS, ACE, CMFM algorithms. These algorithms work only based on spectral image data. In order to evaluate the detection algorithm based on hyper-dimensional feature spaces, Support Vector Machines (SVM) has been implemented which in the case of building detection, it may be regarded as a new application.

The study includes accuracy assessment of effectiveness of SVM with respect to mentioned conventional algorithms regarding the performance indicators. The experiments on the building detection application, using three CASI hyper-spectral images taken from an urban area allow concluding that, SVM is a suitable and effective alternative to conventional detection algorithms.

Key words: CASI hyperspectral image, Building Detection, SVM, Kappa Coefficient.

1. Introduction

Recent advances in hyperspectral sensors with high spectral and spatial resolution have led to an increased interest in exploiting spectral imagery for building detection. They provide plenty of spectral information to uniquely identify materials by their reflectance spectra. A material's reflectance spectrum contains the reflectance values of the material as a function of wavelength (Scharf and Friedlander, 1994).

One of the main challenges in hyperspectral image processing is spectral variability, which refers to the phenomenon that the spectra measured from samples of the same material will never be identical. In other words, spectra of the same material are not fixed due to the inherent variations present in the material. Further spectral variability is introduced by external factors such as atmospheric conditions, sensor noise, and illumination variations (Shaw and Burke, 2003). Although many detection algorithms have been developed over the years, spectral variability poses challenges for these algorithms. Kernel methods have become increasingly popular in a variety of pattern recognition applications. The recently-developed support vector machines (SVM) has its roots in statistical learning theory and is an emerging nonparametric approach for describing a set of data (Tax and Duin, 2004). It has been successfully applied in the areas of facial expression analysis, gene expression data clustering, image retrieval and remote sensing image classification.

Since two decades ago, several researchers have worked in spectral detection subject. Chang and Heinz (2000) studied on three different algorithms of spectral detection on AVIRIS images. Bakker (2002) also studied spectral angle and spectral distance methods as building detection tools in HYMAP hyperspectral images. Lumme (2004) did recognition 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. In all researches, different spectral detection methods have been developed and evaluated. The involved problem here is a significant level of detection error. Therefore, different people have suggested various algorithms to reduce it.

In this study, a special material of building roofs is 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. 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 in building recognition and extraction. We used SVM algorithm to perform building detection in hyperspectral imagery. Experiments on urban scenery confirm that the proposed SVM-based method can provide substantially lower false positive rates (FPRs) while maintaining higher true positive rates (TPRs) when compared to other detectors.

The Section 2 reviews the fundamental of our suggested building detection algorithms. Section 3 provides the experiments and results, and conclusions are discussed in Section 4.

2. Methodology

2.1. Maximum Likelihood Classification

Maximum Likelihood Classification (MLC) is based on probability (Eq. 1). By using this algorithm, a given pixel will belong to a class that shows highest probability.

$$p = -\ln|K_i| - (s-\mu_i)^T K_i^{-1}(s-\mu_i) \qquad (1)$$

Where K and μ are image covariance and mean matrix respectively and s is a pixel vector.

2.2. Modified Spectral Angle Similarity

Using the Modified Spectral Angle Similarity (MSAS) method, given two vectors as building and pixel spectra, a spectral angle between the pair of vectors can be defined. In the case of a hyperspectral image, the "hyper-angle" is calculated by Eq. 2.

$$\alpha = \cos^{-1}(s_i . s_j \,/\, \| s_i \| \| s_j \|) = \cos^{-1}\left(\sum_{l=1}^{L} s_{il} s_{jl} \,/ [\sum_{l=1}^{L} s_{il}^2]^{1/2} [\sum_{l=1}^{L} s_{jl}^2]^{1/2}\right) \tag{2}$$

where L is the number of image bands. The smaller angle means more similarity between the pixel and building spectra. Here, it is preferred to use a modified spectral angle. In above equation, α is between 0 and π/2, then it can be shown that MSAS= $\frac{2\alpha}{\pi}$. By this rescaling, the values of the measure convert to [0, 1].

2.3. Adaptive Coherence Estimator

The aim of the Adaptive Coherence Estimator (ACE) statistic is to detect the presence of a building vector S_i in a measurement or test vector S_j by comparing the statistic with a threshold (Scharf and McWhorter, 1996). The detection must be performed in the presence of noise, clutter, and interference. The ACE statistic used in this study is (Eq. 3):

$$ACE = \frac{(S_i^T K_{L\times L}^{-1} S_j)^2}{(S_i^T K_{L\times L}^{-1} S_i)(S_j^T K_{L\times L}^{-1} S_j)} \tag{3}$$

Training data vectors are used to construct a sample covariance *K*.

2.4. Covariance-based Matched Filter Measure

Covariance-based Matched Filter Measure (CMFM), measures the similarity of vectors s_i and s_j (s is spectral properties) after subtraction of their mean μ (Eq. 4).

$$CMFM = (s_i - \mu)^T K_{L\times L}^{-1} (s_j - \mu) \tag{4}$$

Where $K_{L\times L}^{-1}$ 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 building class.

2.5. Support Vector Machine

The Support Vector Machine (SVM) based approach finds the optimal separating hyperplane between building and background classes by focusing on the training cases that lie at the edge of the class distributions (the support vectors), while ignoring other training cases effectively. In soft-margin SVM that data is often not linearly separable, the optimization problem becomes in the form of minimization of $\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i$ subject to $y_i(w^T x_i + b) \geq 1 - \xi_i \quad \xi_i \geq 0$ where $\xi_i \geq 0$ is slack variable. The constant $C > 0$ sets the relative importance of maximizing the margin and minimizing the amount of slack.

The training data may be projected onto a high dimensional, Hilbert space, H, through a mapping function φ, or $\varphi : R^q \rightarrow H$. An input data point x can be represented as $\varphi(x)$ in the high dimensional space H. The expensive computation of $(\varphi(x), \varphi(x_i))$ in the high dimensional space is reduced by using a positive definite kernel such that, $(\varphi(x),\varphi(x_i))=k(x, x_i)$ leading to decision functions of the form,

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{r} \alpha_i y_i k(x, x_i) + b) \quad (5)$$

Where α_i, i=1,…,r are lagrange multipliers (DeCoste and Weston 2007). To train the classifier (Eq. 5), only the kernel is required and no explicit knowledge of φ is needed. A kernel that can be used to construct a SVM must meet Mercer's condition (Vapnik, 1995) and one such kernel is the radial basis function, $k(x,x_i) = e^{-\gamma\|(x-x_i)\|^2}$ where γ is a parameter controlling the width of the Gaussian kernel. The accuracy of detection by a SVM is dependent on the magnitude of the parameters C and γ and these are often selected on the basis of a cross-validation analysis.

3. Experiments

3.1. HIS Data

The MLC, MSAS, ACE, CMFM and SVM techniques have been applied on Compact Airborne Spectrographic Imager (CASI) hyperspectral images. CASI has a flexible spectral resolution capability. It means that the image data may have different number of bands (maximum 288). These numbers of bands cover a range from 0.4 to 1.0 µm of electromagnetic spectrum; with the width of each band 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 range of sensor is another parameter which produces the image data with 12 bits or 4096 gray levels. CASI also is equipped by GPS and INS for On/Off fly rectification and geo-referencing of images. The data used in this study are three set of CASI images. The spatial resolution of images is 2m and the numbers of bands for these images are 32. The images size are 128×128 pixels each (Fig. 1 (1)). A spectrum of building materials has been extracted by collecting and averaging the spectra of manually selected pixels for sample data (Fig. 1 (3)).

3.2. Experimental Results

Fig.2 shows the result maps for each method. To compare and evaluate the results, we extracted a true data map by visual interpretation of the building materials of the scene (Fig. 1 (2)).

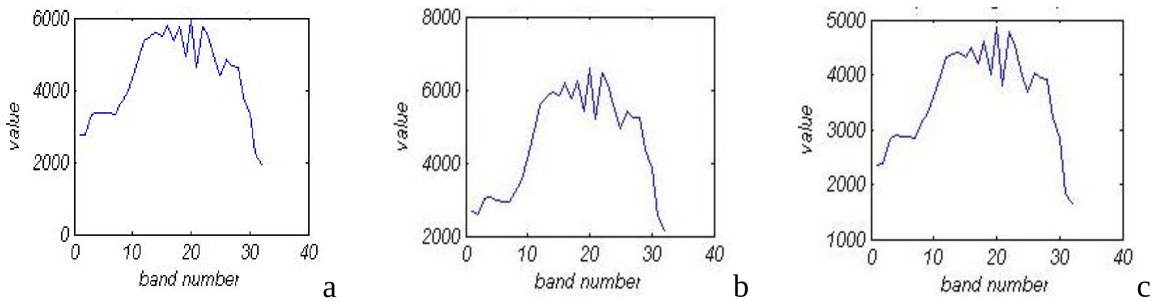
The γ parameter of radial basis function kernel and *C* parameter for SVM approach were determined using a five-fold cross-validation approach. The used values in this detector are shown in table 1.

Table 1. *C* and *γ* values of SVM detector.

	C	*γ*
Image 1	0.25	0.005
Image 2	0.30	0.004
Image 3	0.25	0.007

(1)

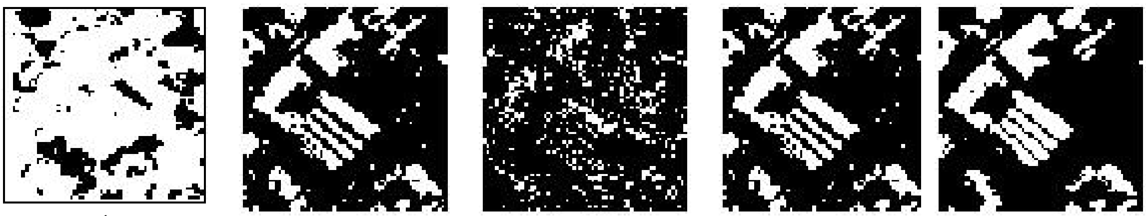
(2)



(3)

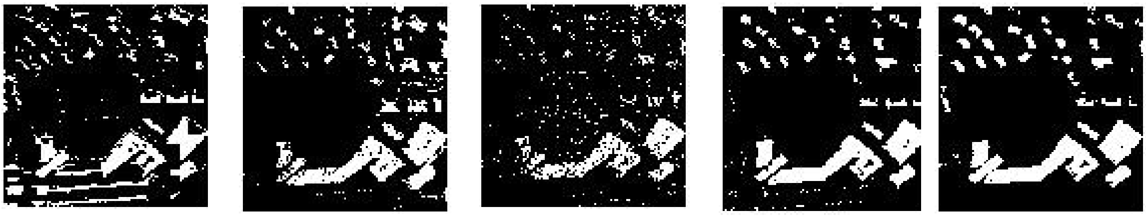
Fig 1: (1) The false color CASI image of study area (R=0.914, G=0.620, B=0.451),
(2) Ground truth data, and
(3) Extracted spectra of building material (a) image1, (b) image2, and (c) image3

For a quantitative evaluation of the results, we retain two elements of the confusion matrix: overall accuracy (OA), and kappa coefficient (K). The overall accuracy is calculated by summing the number of both building and background pixels correctly classified and dividing the result by the total number of pixels. Since OA is not a very complete and reliable criterion, the Kappa coefficient is computed with other elements of the confusion matrix.



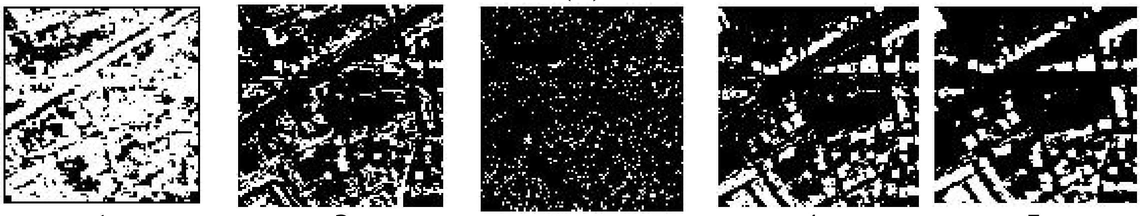
1 2 3 4 5

(A)



1 2 3 4 5

(B)



1 2 3 4 5

(C)

Fig 2: The resulting images of performing algorithms: (1) MLC, (2) MSAS, (3) ACE, (4) CMFM, (5) SVM, (A) image 1 (B) image2 (C) image3.

It can be seen that the SVM method has produced less noisy results. From Table 2, we can see that the two quality criteria, OA and K, for SVM are better than other four approaches. In all resulting maps, there are some identified pixels which are relatively similar to building class but not complete. For MLC and ACE methods, the building maps have produced a lot of mismatching. However, the MSAS results are more precise. When comparing the results obtained from the three data sets, it can be seen that the maps for image 2 are less noisy than the other two images. It is probably due to the less dense imaging scene.

Table 2. Computed quantities in assessing the experiments accuracies.

	Image1		**Image2**		**Image3**	
Algorithm	**Overall Accuracy**	**Kappa Coefficient**	**Overall Accuracy**	**Kappa Coefficient**	**Overall Accuracy**	**Kappa Coefficient**
ML	**0.61**	**0.28**	**0.92**	**0.69**	**0.58**	**0.28**
MSAS	**0.88**	**0.71**	**0.96**	**0.82**	**0.85**	**0.70**
ACE	**0.76**	**0.39**	**0.94**	**0.77**	**0.57**	**0.25**
MCMF	**0.90**	**0.78**	**0.97**	**0.85**	**0.90**	**0.78**
SVM	**0.92**	**0.83**	**0.98**	**0.89**	**0.92**	**0.81**

4. Conclusions

This study shows the possibility of extracting useful information on environmental characterization of urban areas from hyperspectral data. In this type of application, any applied algorithm is responsible to detect only one certain class (i.e. buildings) using spectral information. Therefore, regarding the high volume of hyperspectral images and the required speed when using desired algorithm, it is expected more than other applications to achieve the most accurate results.

Using SVM method in building detection, the experiments demonstrated noticeable improvement on the accuracy in comparison to the other methods. In assessing accuracies among detection methods, SVM method presented the best results with Kappa coefficient 83%, 89% and 81% in images 1, 2 and 3 respectively.

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