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Support Vector Machines for Object Based Building Extraction in Suburban Area using Very High Resolution Satellite Images, a Case Study: Tetuan, Morocco

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ABSTRACT

Many fields of artificial intelligence have been developed such as computational intelligence and machine learning involving neural networks, fuzzy systems, genetic algorithms, intelligent agents and Support Vector Machines (SVM). SVM is a machine learning methodology with great results in image classification. In this paper, we present the potential of SVMs to automatically extract buildings in suburban area using Very High Resolution Satellite (VHRS) images. To achieve this goal, we use object based approach: Segmentation before classification in order to create meaningful image objects using color features. In the first step, we form objects with the aid of mean shift clustering algorithm. Then, SVM classifier was used to extract buildings. The proposed method has been applied on a suburban area in Tetuan city (Morocco) and 83.76% of existing buildings have been extracted by only using color features. This result can be improved by adding other features (e.g., spectral, texture, morphology and context).

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1. INTRODUCTION

In the last decades, many fields of artificial intelligence have been developed such as computational intelligence and machine learning involving neural networks, fuzzy systems, genetic algorithms, intelligent agents and Support Vector Machines (SVM) [1]. Machine learning is an integral part of pattern recognition, and in particular classification [2]. SVM is a theoretically superior machine learning methodology with great results in the classification of high-dimensional datasets and has been found competitive with the best machine learning algorithms [3]. In many studies, SVMs were tested and evaluated as image classifier [4-12].

Since the year 2000, Very High Resolution (VHR) optical sensors such as IKONOS [13], QUICKBIRD [14], WORLDVIEW2 [14], GEOEYE [13], and more recently PLEIADES [15] have been launched (Table 1). Their sub-metric spatial resolution has become a viable alternative and complementary to aerial photography for several applications [16; 17] and has increased the range of applications where Remote Sensing (RS) data can be usefully employed.

Building extraction is one of the main procedures used in updating digital maps and Geographic Information System (GIS) database information [18]. It is an active research field in Computer Vision (CV) and RS. Full automatic systems in this field are not yet operational [19] and cannot be implemented in a single step [20]. The reason behind such difficulties is that buildings have homogeneous spectral features with other man-made objects, such as squares and roads [21]. Otherwise, buildings can constitute complex structures that create difficulties (e.g., discontinuities, occlusions, shadows [22]) due to its variation in shape, size, and spectral response [23].

Table 1. Very High Resolution Satellites (VHRS) bands with their corresponding characteristics [company, orbit (km), launch date, scan-width (km²/day), projection, datum and band resolution (m)].

Satellite			WORLDVIEW 2	GEOEYE 1	QUICKBIRD	IKONOS	PLEIADES 1
Company	DigitaleGlobe		X		X		
	GeoEye			X		X	
	European Space Agency						X
Orbit (km)			770	684	450	681	694
Launch date			2010	2009	2002	1999	2012
Scan-width (km²/day)			975 000	700 000			
Projection	UTM, Lat/Long, StatePlane		X	X	X		X
	UTM,Geographic, StatePlane					X	
Datum	Nad 27, 83, WGS 84		X	X		X	X
	Nad 83, WGS 84				X		
Band	Pansharpening Resolution (m)		0.5	0.5	0.6	1	0.5
	Spectral Resolution (nm)	Blue	450-510	450-510	450-520	450-520	430-550
		Green	510-580	510-580	520-600	520-600	490-610
		Red	630-690	655-690	630-690	630-690	600-720

Many studies try to develop robust building detection algorithms [18; 24-30]. Pixel-based classification has been used to detect buildings [31; 32], however this method involves drawbacks such as (e.g., salt and pepper effect) [33] in VHR satellite data. To tackle this problem, most studies considere the building as objects, and automatic segmentation is used to create the image-objects. Object-based approach defines the image-objects using features based on the spectral response, the image texture, or the shape of the objects [17; 34; 35], or using features of wavelet transform [36; 37]. Other studies use multi-scale segmentation techniques [38; 39]. Stassopoulou and Caelli [34] included auxiliary data such as road maps. Morphological filtering techniques, or Hough transform, are applied to generalize and smooth the shape of those objects classified as buildings [17; 40; 41]. L'Homme et al. [42] proposed a building extraction method using the variance of the Grey Level Co-occurrence Matrix (GLCM). Hermosilla et al. [16] used an object-based image classification: segmentation, feature extraction and selection, and classification to detect buildings.

The main objective of this study is to present the potential of SVMs to automatically extract buildings in suburban area in Tetuan city (Morocco) landscape. The study was made through object based approach: Segmentation before classification. In this research, only color features were considered.

2. DATA AND STUDY AREA

a. Data

The launch of satellites with very high spatial resolution allows working on images whose resolution is metric or sub metric. Objects such as buildings and roads are now available. The main problem with this type of data is now the cost of acquisition and repeatability especially if we are interested in multi-temporal studies [43]. To solve this financial constraint, the possibilities offered by Google Earth © [44] have been explored. This product, in addition to its growing popularity among the general public, it interests also the scientific community [45; 46]. However, the radiometric parameters are not clearly specified by Google Earth ©. Only color images are provided, therefore a spectral study cannot be carried out. Data corresponding to GEOEYE 1 satellite of August 3, 2010 has been used (Table 1).

b. Study Area

The study area covers 0.5 km^2 of a suburban area in Tetuan city (Morocco) characterized by residential strip with detached and semi-attached buildings to accommodate families (Figure 2).

Figure 2. Suburban study area in Tetuan city (Morocco): (Lat: 35.601346, Long: -5.320952)

3. OBJECT BASED APPROACH

3.1. Support Vector Machines

Support Vector Machine (SVM) is a supervised non-parametric statistical learning technique, therefore there is no assumption made on the underlying data distribution. In its original formulation [47] the method is presented with a set of labeled data instances and the SVM training algorithm aims to find a hyperplane that separates the dataset into a discrete predefined number of classes in a fashion consistent with the training examples [48].

In its simplest form, SVMs are linear binary classifiers that assign a given test sample a class from one of the two possible labels. Let us consider a supervised binary classification problem. If the training data are represented by: $\{x_i, y_i\}, i = 1,2, \ldots, N$ and $y_i \in \{-1, +1\}$, where N is the number of training samples, $y_i = +1$ for class w_1 and $y_i = -1$ for class w_2. Suppose the two classes are linearly separable. This means that it is possible to find at least one hyperplane defined by a vector W with a bias W_0, which can separate the classes without error:

$$f(x) = W.x + W_0 = 0 \quad (1)$$

Where f(x) is the discrimination function associated to the hyperplane. To find such a hyperplane, W and W_0 should be estimated in a way that:

$$y_i(x_i + W_0) \geq +1 \text{ for } y_i = +1 \text{ (class } w_1) \quad (2)$$

$$y_i(x_i + W_0) \leq -1 \text{ for } y_i = -1 \text{ (class } w_2). \quad (3)$$

Combining (2) and (3), we obtain:

$$y_i(W.x_i + W_0) - 1 \geq 0 \quad (4)$$

Many hyperplanes could be fitted to separate the two classes, instead there is only one optimal hyperplane that is expected to generalize better than other hyperplanes [48].

The goal is to search for the hyperplane that leaves the maximum margin between classes (Figure 3). To be able to find the optimal hyperplane, the support vectors must be defined. The support vectors lie on two hyperplanes which are parallel to the optimal one and are given by:

$$W.x_i + W_0 = \pm 1 \quad (5)$$

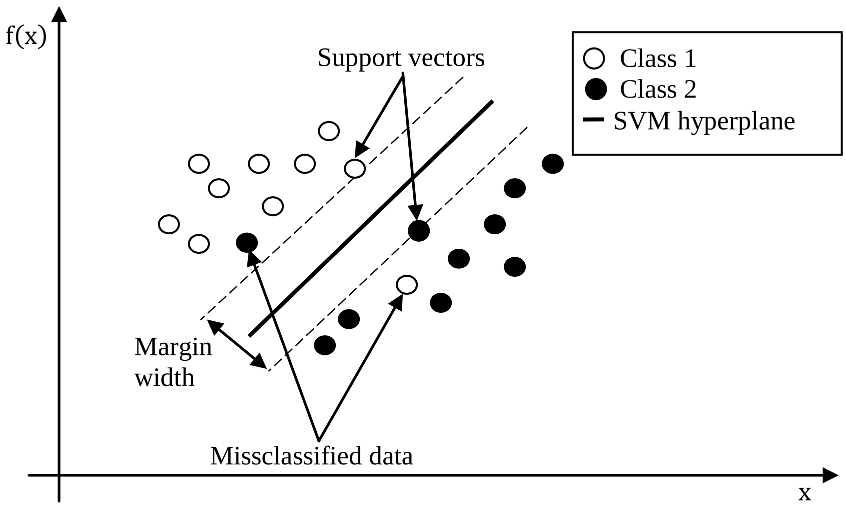


Figure 3. Linear SVM example. Source: adapted from [48]

If a simple rescale of the hyperplane parameters W and W_0 takes place, the margin can be expressed as $2/\|W\|$. The optimal hyperplane can be found by solving the following optimization system:

$$\begin{cases} \min: \frac{1}{2}\|W\|^2 \\ y_i(W.x_i + W_0) - 1 \geq 0; i = 1,2, \dots N \end{cases} \quad (6)$$

The implementation of a linear SVM assumes that the multispectral feature data are linearly separable in the input space. In practice, data points of different class memberships overlap one another. This makes linear separability difficult as the basic linear decision boundaries are often not sufficient to classify patterns with high accuracy. Techniques such as soft margin and the kernel trick methods are used to solve the inseparability problem by introducing additional variables in SVM optimization and mapping [48].

For applying SVM to multi-class classifications, two main approaches have been suggested. The basic idea is to reduce the multi-class to a set of binary problems so that the SVM approach can be used. The first approach is called “one against all”. In this approach, a set of binary classifiers is trained to be able to separate each class from all others. The second approach is called “one against one”. In this approach, a series of classifiers is applied to each pair of classes, with the most commonly computed class kept for each object [3].

3.2. Segmentation

Image segmentation in general is defined as a process of partitioning an image into homogenous regions, which allows the use of a number of features on top of spectral features such as texture, morphology and context. The segmentation technique used in this study is a Mean Shift (MS) technique implemented in the open source library Orfeo ToolBox OTB [49]. Within the feature space, the MS [50] operates by estimating in an iterative way the local maxima of the underlying nonparametric feature distribution. Two parameters have to be fixed: i) the spatial radius (used for defining the neighborhood), and ii) the spectral radius (used for defining the interval in the color space).

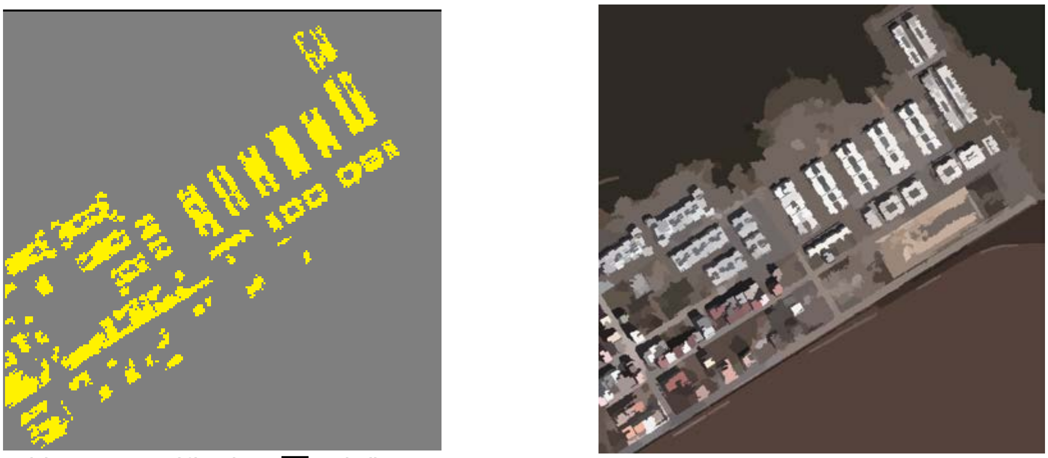
3.3. Classification

The classification was performed in the OTB open source library with a SVM classifier. Since the main objective is to evaluate building detection, only two classes were considered: buildings and non-buildings areas. Since we have a color image of the study area, only color features were used. Training set was carried out manually.

4. RESULTS AND ANALYSIS

4.1. Object-Based Classification

A spatial radius of 10 and a spectral radius of 30 were selected in the MS segmentation. In this study, as mentioned in section 3.3 only two classes were used: buildings and non-buildings. The SVM classification and the MS segmentation results are shown in Figure 4.



(a) SVM classification: Buildings
Non-buildings

(b) MS segmentation with spatial radius of 10 and spectral radius of 30.

Figure 4. (a) SVM classification, and (b) MS segmentation results

4.2. Accuracy Assessment

The error matrix has been generated to evaluate the results of SVM classification (Table 2). Only the accuracy of buildings class was considered because the main objective of our study is building extraction. The reference samples are generated by visual interpretation.

The results show that buildings were classified with user accuracy of 85.71% and producer accuracy of 81.81%. In general, taking the average of both accuracies buildings are extracted with an overall accuracy of 83.76%.

In conclusion, SVM classification shows high efficiency for building extraction when the parameters are properly adjusted and adapted to the type of urban landscape considered.

Table 2. Accuracy assessment results

	Reference data		
Classified data	Buildings	Non-buildings	User's accuracy
Buildings	36	6	**85.71%**
Non-buildings	8	-	-
Producer's accuracy	**81.81%**	-	
		Overall building extraction accuracy: **83.76%**	

5. CONCLUSION

The main objective of this study is to present the potential of SVMs to automatically extract buildings in suburban areas using VHRS applied in Tetuan city (Morocco) landscape. The study was made through object based approach: Segmentation before classification in order to create meaningful image objects. In this research, color features only were considered. Segmentation was implemented by MS algorithm and SVM classifier was used for classification.

The results obtained show an overall building extraction accuracy of 83.76% as consequence of just using color features. Adding others features (e.g., spectral, texture, morphology and context) can provide more accurate results. These methodologies can be applied to the detection of new buildings for updating GIS databases, as well as change detection.

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