TREE CROWN DELINEATION ON VHR AERIAL IMAGERY WITH SVM CLASSIFICATION TECHNIQUE OPTIMIZED BY TAGUCHI METHOD: A CASE STUDY IN ZAGROS WOODLANDS

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ABSTRACT:

The Support Vector Machine (SVM) is a theoretically superior machine learning methodology with great results in classification of remotely sensed datasets. Determination of optimal parameters applied in SVM is still vague to some scientists. In this research, it is suggested to use the Taguchi method to optimize these parameters. The objective of this study was to detect tree crowns on very high resolution (VHR) aerial imagery in Zagros woodlands by SVM optimized by Taguchi method. A 30 ha plot of Persian oak (*Quercus persica*) coppice trees was selected in Zagros woodlands, Iran. The VHR aerial imagery of the plot with 0.06 m spatial resolution was obtained from National Geographic Organization (NGO), Iran, to extract the crowns of Persian oak trees in this study. The SVM parameters were optimized by Taguchi method and thereafter, the imagery was classified by the SVM with optimal parameters. The results showed that the Taguchi method is a very useful approach to optimize the combination of parameters of SVM. It was also concluded that the SVM method could detect the tree crowns with a KHAT coefficient of 0.961 which showed a great agreement with the observed samples and overall accuracy of 97.7% that showed the accuracy of the final map. Finally, the authors suggest applying this method to optimize the parameters of classification techniques like SVM.

1 INTRODUCTION

Recently, remote sensing has increasingly become a prime source of land cover information (Kramer, 2002). This has been made possible by developments in satellite sensor technology which leads to enabling the acquisition of land cover information over large areas at different radiometric, spectral, spatial and temporal resolutions. The procedure of relating the pixels in a satellite image to known land cover classes is called image classification and the algorithms used to perform the classification process are called image classifiers (Mather, 1987). Estimation and mapping of forest resources is vital for management, planning and research in these valuable ecosystems.

One of the most important parameters in forests is canopy cover, especially in woodlands. Forest canopy is defined as the top layer of a forest or wooded ecosystem consisting of overlapping leaves and branches of trees, shrubs, or both (Lowman and Wittman, 1996; Zeng et al., 2008). Field measurements in these cases are very time consuming and labour intensive (Biondi et al., 1994). Remote sensing is one of the most powerful methods used in forest studies. Many remote sensing applications involve estimation of either canopy cover or individual tree canopy area as an intermediate stage in distinguishing the signals reflected from forest canopy and forest floor (Korhonen et al., 2006). One of the main and commonly used image classification techniques are pixel-based approaches.

Support Vector Machine (SVM) is a superior pixel-based image classification method, demonstrating a set of theoretically great machine learning algorithms. SVMs have their roots in Statistical Learning Theory (Vapnik, 1995). They have been extensively applied to machine vision fields such as character, handwriting digit and text detection (Joachims, 1998), and more recently to satellite image classification. The SVM technique is powerful like Artificial Neural Networks and other nonparametric classifiers (Foody and Mathur, 2004).

SVMs function by nonlinearly projecting the training data in the input space to a feature space of higher (infinite) dimension by use of a kernel function. This procedure results in a dataset linearly separable that can be separated by a linear classifier. SVMs belong to the general category of kernel methods. A kernel method is an algorithm that depends on the data only through dot products. When this happens, the dot product can be replaced by a kernel function which computes a dot product in some possibly high dimensional feature space. This replacement has two advantages: first, the capability to generate nonlinear decision boundaries using methods designed for linear classifiers; second, the application of kernel functions allows the user to apply a classifier to data that have no obvious fixed-dimensional vector space representation. The example of such data are sequence, DNA or protein, and protein structure in bioinformatics.

More formally, a support vector machine constructs a hyperplane or a set of hyperplanes in a high- or infinite-dimensional space, which can be applied for regression and classification or even other tasks. Instinctively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin) because the larger the margin the lower the generalization error of the classifier.

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The development of SVM was initially triggered by the exploration and formalization of learning machine capacity control and over-fitting issues (Vapnik, 1998). One of the most important challenges in this case is determination of the optimum combination of affecting parameters on the performance of SVM classification approach that can not be performed by trial and error approaches. Fractional factorial design of experiments such as Taguchi method can be an effective way to cope with this problem.

As mentioned before, SVM classification is essentially a binary (two-class) classification technique, which has to be modified to handle the multiclass tasks in real world situations e.g. obtaining land cover information from satellite images. Taguchi (1990) developed a family of FFE matrices that could be utilized in various situations. This method has been generally adopted to optimize the design parameters (based on a signal to noise parameter) and significantly minimize the overall testing time and the experimental costs (Erzurumlu and Ozcelik, 2006; Wang and Huang, 2007; Chou et al., 2009; Yang et al., 2011; Sadeghi et al., 2012) following a systematic approach to confine the number of experiments and tests.

The aim of this study was to delineate tree crowns on very high resolution (VHR) aerial imagery newly taken in Iran applying SVM classification approach. In addition, it was aimed to optimize the effective parameters of SVM by Taguchi method to find a robust procedure to apply SVM on VHR aerial imagery.

2 METHODOLOGY

2.1 Study Area

The study site is located in Yasuj city, Kohgiluye-va-BoyerAhmad province, Iran between 51° 36´ 42” to 51°37´ 01” E and 30° 37´ 31” to 30° 37´51” N (Fig. 1). The minimum elevation is 1150 m and the maximum one is 1380 m. The mean annual precipitation and temperature are 460 mm and 24.6 °C, respectively. A 30 ha plot fully covered with Persian oak (*Quercus persica*) as the most frequent tree species in Zagros woodlands, was selected for this research (Fig. 2). Most of the trees have coppice structure in this region with lots of branches and round crowns.

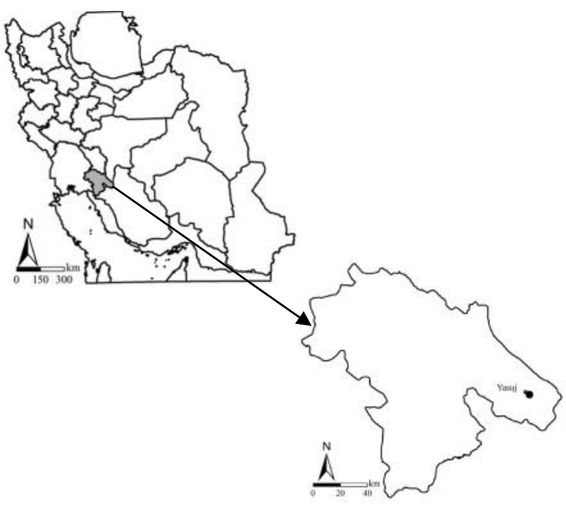

Figure 1: The study area in Kohgiluye-va-BoyerAhmad province and Iran.

Figure 2: Persian oak trees in the study area.

2.2 Materials and Methods

VHR aerial imagery newly taken in Iran was applied in this study to investigate its potential to measure canopy cover in Zagros woodlands. As these data has very high spatial resolution (0.06 m), it is expected to detect and extract crown boundaries more precisely compared to other remote sensing data. The FL (Focal Length) and IFOV (Instant Field of View) of camera used to take this imagery are 101.4 mm and 37°, respectively. The resulting imagery has 7500 × 11500 pixels with 5 panchromatic, RGB and infrared bands. The height of the plane carrying the camera is about 700 m a.s.l. The applied imagery was taken in 22 Dec. 2008 and their scale is 1:7000.

Classifying the imagery, three essential steps were conducted i.e. selection of training samples which were representative for different information classes; executing classification algorithms and as a final step, assessing the accuracy of the classified image through analysis of a confusion matrix (Tso and Mather, 2009). SVM is a supervised classification system developed on statistical learning theory that provides good classification results from complex data (Bai et al., 2012). This method uses two classes (e.g. presence/absence) of training samples within a multidimensional feature space to fit an optimal separating hyperplane and tries to maximize the margin that is the distance between the closest training samples, or support vectors, and the hyperplane itself (Pouteau et al., 2012). There are four kernel types in SVM including Linear, Polynomial, Sigmoid, Basis Function, and Radial. All of these are different ways of mathematically representing a kernel function (Hsu et al. 2007). This approach is a binary classifier in which n-class problems can be transformed into the sequence of n binary classification tasks (Belousov et al., 2002). The SVM differs from other separating hyper-plane approaches in the way the hyper-plane is constructed from the training points (Marjanović et al., 2011). Figure 3 shows the schematic illustration of SVM. In the SVM classification technique, Kernel function, Gamma, penalty parameter, pyramid level and Pyramid reclassification threshold should be optimized. A L32 orthogonal array was applied to optimize SVM parameters according to the factors and levels mentioned in Table 1.

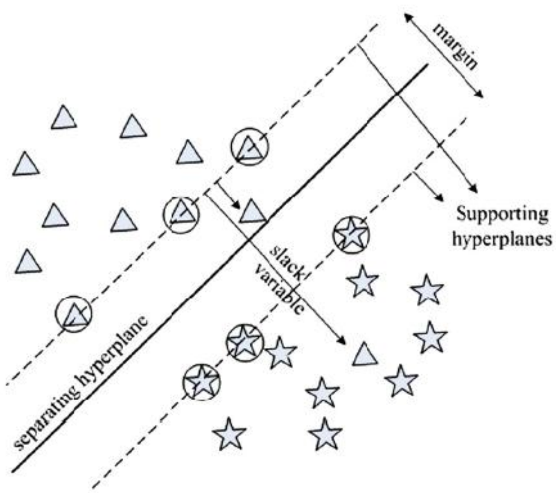

Figure 3: The schematic illustration of SVM.

Factor	Description	Level 1	Level 2	Level 3	Level 4
A	Kernel function	Polynomial	RBF	-	-
B	Gamma	0.1	0.3	0.5	0.7
C	Penalty parameter	10	100	1000	10000
D	Pyramid levels	1	2	3	4
E	Pyramid reclassification threshold	0.3	0.5	0.7	0.9

Table 1. Factors and their levels used for optimization in pixel-based and object oriented techniques.

In the next step the classification tests were performed according to the Taguchi orthogonal array and thereafter, an analysis of the signal-to-noise (S/N) ratio was used to evaluate the classification results. In order to assess the accuracy of the classified image, confusion matrixes were applied for SVM approach.

To achieve Taguchi ability, as many factors as possible should be considered, and non-significant variables must be recognized at the first prospect. Thus, the Taguchi method creates a standard orthogonal array to accommodate these requirements. Based on the number of factors and levels needed, the user can select the standard orthogonal array. Using the orthogonal array particularly designed for the Taguchi method, the optimal experimental conditions can be simply determined.

The Taguchi method has been extensively and successfully used for determination of the optimum process parameters in different subject areas such as aerospace (Singaravelu et al., 2009), food (Sahin et al., 2007), sports (Burton et al., 2010), communications (Al-Darrab et al., 2009), environment (Aber et al., 2010; Zolfaghari et al., 2011), construction (Türkmen et al., 2008), energy (Chang et al., 2009; Zeng et al., 2010), material manufacturing (Dingal et al., 2008), milling (Zhang et al., 2007), welding (Lakshminarayanan and Balasubramanian, 2008), mechanical engineering (Palanikumar et al., 2008; Hascalik and Caydas, 2008; Rosa et al., 2009), dental science (Lin et al., 2007; Geerts Greta et al., 2008) and soil erosion and sediment yield (Sadeghi et al., 2012). However, no application of the Taguchi method to tree crown and forest studies has been reported until the present time. In the last step, the classification accuracy was investigated by confusion matrix method. To obtain this matrix, 600 random points were applied on the classified imagery and in the field. In this step the misclassification of the objects that were aimed to be detected on the imagery could be revealed to evaluate the efficiency of the SVM technique optimized by the Taguchi method. Two indices of overall accuracy and KHAT coefficient were calculated to analyse different aspects of the final map. The first index shows the accuracy of the map (versus its error) and it contains the commission and omission mistakes. Also the producer and user accuracies were estimated applying the confusion matrix. The later one shows the agreement between the ground truth (GT) and the results of the classified VHR imagery by SVM (Paine and Kiser, 2012). To figure out how these indices are calculated, please refer to Paine and Kiser, 2012, pp. 471-473.

3 RESULTS

As already explained, 32 classification tests were conducted for SVM approach according to the Taguchi orthogonal array. The optimum conditions for SVM approach areas were as following: (1) Kernel function: RBF; (2) Gamma: 0.3; (3) Penalty parameter: 100; (4) Pyramid levels: 1 and (5) Pyramid reclassification threshold: 0.9.

After classification of the mentioned VHR aerial image, all other objects than canopy cover have been merged, because the objective of this study was to produce canopy cover maps. Figure 4 shows the best SVM classification result that the blue class was the woodland floor, the green parts were tree crowns and the red class was the shadow of the trees (Fig. 5).

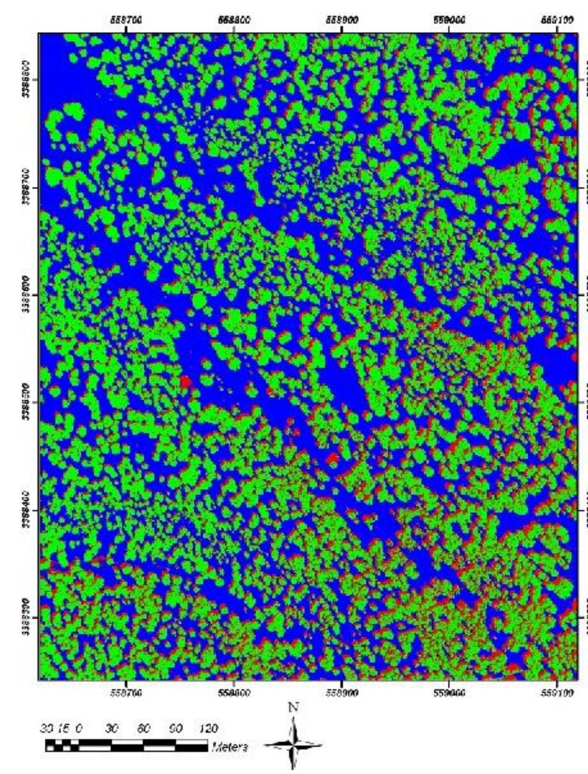

Figure 4: The best classification results of the VHR imagery by SVM.

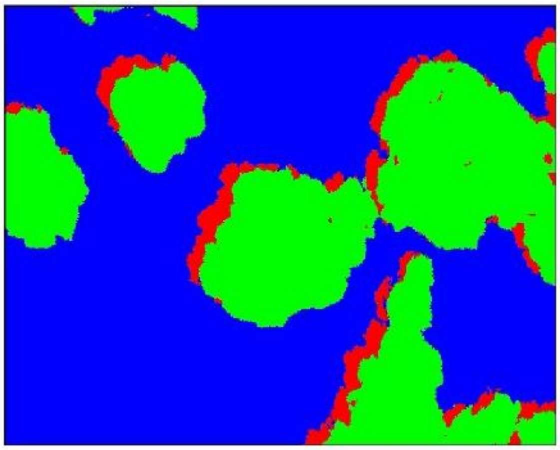

Figure 5: Three classes of tree crowns (green); tree shadows (red) and woodland floor (blue).

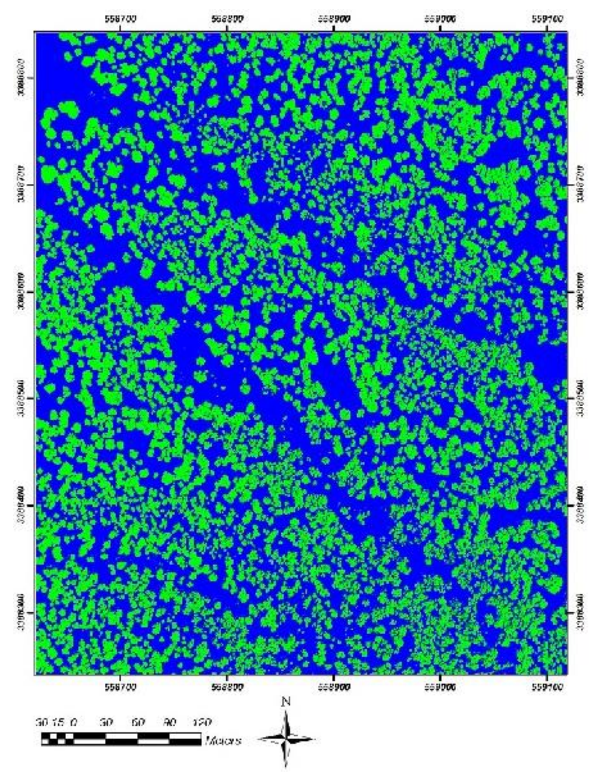

Figure 6: The canopy cover map of the study area.

Figure 6 also shows the final canopy cover map after merging the woodland floor and tree shadows. In this map, the green parts are “tree crowns” and the blue parts are “other features”. Figure 7 illustrates the overlay of a part of the canopy cover map on the original image. As seen in this figure, the boundaries of tree crowns were detected very well and it was separated from the shadow completely. It also should be mentioned that it is not possible to determine the boundaries of tree crowns in filed measurements. This is one the advantages of remotely sensed datasets that make this possible and it facilitates canopy cover studying.

Figure 6: A part of VHR imagery classified by SVM optimized by the Taguchi method.

It was necessary to evaluate the agreement of the final canopy map with the field measurements of this research. To find out the amount of agreement between the canopy map and GT, 600 random points were investigated to make the related confusion matrix. Table 2 shows the summary of confusion matrix of the canopy map resulted from VHR aerial imagery classified by SVM technique and the filed measurements. Two important indices of overall accuracy and KHAT coefficient were calculated by Table 2.

These indices were 97.7% and 0.961 respectively. The user accuracy and producer accuracy of the final canopy cover map were calculated by Table 2 (Table 3). As observed in Table 3, the user and producer accuracies of shadow were the lowest between three classes of trees, shadows and floor. The highest user and producer accuracies were obtained in trees and woodland floor classes, respectively. These indices also showed that the boundaries of trees were detected with high accuracy that made the map suitable enough for further studies on canopy cover of the study site.

SVM	**Tree**	**Shadow**	**Land**	**X_{i+}**
Trees	195	0	1	196
Shadows	2	98	4	104
Floor	3	4	293	300
X_{+i}	200	102	298	600

Table 2: Confusion matrix of the SVM classification approach.

	User accuracy (%)	**Producer accuracy (%)**
Trees	99.5	97.5
Shadows	94.2	96.1
Floor	97.7	98.3

Table 3: The user accuracy and producer accuracy of the canopy cover map.

4 CONCLUSION

Forest canopy defined as the area occupied by the vertical projection of tree crowns, is a common concept in forestry and of wide interest in both scientific studies and political decisions. Also it has recently become an important part of forest inventories (Korhonen et al. 2006; Zeng et al., 2008) especially in Zagros woodlands because of its great role in sustainable management of these socially and economically valuable ecosystem.

It was aimed to extract the crowns of coppice trees in Zagros woodlands on VHR aerial imagery by SVM classification technique. In order to optimize the effective parameters of SVM, the Taguchi method was utilized. The controllable parameters were mentioned in Table 1. The optimal amount of each parameter were determined via the Taguchi method and their values were (1) Kernel function: RBF; (2) Gamma: 0.3; (3) Penalty parameter: 100; (4) Pyramid levels: 1 and (5) Pyramid reclassification threshold: 0.9. Thereafter, the optimized SVM technique was utilized to classify the VHR imagery to obtain the canopy cover map of the study area. The application of the Taguchi method to optimize SVM parameters has not been observed in any research and it was firstly performed in the present study.

SVM has often provided better classification results that other widely used classification techniques, although, it is not easy to find an optimal combination of parameters needed to apply this technique. The robust procedure suggested in this paper can help scientists use this technique to classify VHR aerial imagery or even other remotely sensed datasets.

The results showed that the optimized SVM technique could detect the crowns of coppice Persian oak trees in the study area. It also could separate the shadows of the trees very well (Fig. 4 and 5). Although it is believed that studying the tree crowns on remotely sensed datasets is more precise than field measurements (Paine and Kiser, 2012), the suggested procedure on VHR imagery makes this study much more accurate because of detecting crown boundaries due to the high spatial resolution of the applied imagery and in favour of the optimized classification technique suggested in this paper.

The results showed that the Taguchi method is a very useful and time and effort saving approach to optimize the combination of parameters affecting the performance of SVM classification technique. The final canopy cover map obtained by SVM technique optimized by the Taguchi method was evaluated by confusion matrix method. It was concluded that the map had a great agreement with the GT (KHAT coefficient of 0.961) with an overall accuracy of 97.7%. The results also showed that the users who are interested in studying the canopy of the Persian oak trees in the study area can trust the results due to the high user accuracy of tree crowns as mentioned in Table 3. It also should be explained that the reflectance of the shadows and the woodland floor were so similar that made the second class have the lowest producer and user accuracies. The commission and omission mistakes were 4 between the shadows and woodland floor which proves the lowest producer and user accuracies of the second class.

It should also be mentioned that because of the high spectral variance of VHR imageries, there are some deficiencies in pixel-based approaches (Schowengerdt, 2007). In fact, the spectral characteristics of pixels are involved in the classification process in these methods. Therefore, the inter-class spectral variance in VHR imageries causes several misclassifications. Object-oriented approaches can be a good idea to deal with this problem. Therefore, application of object-oriented approaches can be suggested for future works.

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