

Support vector machine as a binary classifier for automated object detection in remotely sensed data

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Abstract. In the present paper, author proposes the application of Support Vector Machine (SVM) for the analysis of satellite imagery. One of the advantages of SVM is that, with limited training data, it may generate comparable or even better results than the other methods. The SVM algorithm is used for automated object detection and characterization. Specifically, the SVM is applied in its basic nature as a binary classifier where it classifies two classes namely, object and background. The algorithm aims at effectively detecting an object from its background with the minimum training data. The synthetic image containing noises is used for algorithm testing. Furthermore, it is implemented to perform remote sensing image analysis such as identification of Island vegetation, water body, and oil spill from the satellite imagery. It is indicated that SVM provides the fast and accurate analysis with the acceptable result.

1. Introduction

The remotely sensed data provide the detailed and reliable view of the Earth's that helps in analysing various problems related to earth science and other disciplines. The success of the rapid development of satellite sensor technology has been followed with the advancement in image analysis technique that enhance the quality of remote sensing product. In the remote sensing image analysis context, image classification is one of the rapidly developed subjects.

Various techniques had been developed in the recent decades, aiming at finding the the most efficient algorithm delivering the accurate result. Remote sensing image classification is typically originated to convert the data recorded by the sensor into several classes of objects. Nevertheless, the process is not trivial. In supervised technique, for instance, the requirement of large amount of the training samples makes the classification process daunting [1].

Among the classification techniques, Support Vector Machine (SVM) has gained the increasing popularity in the recent years. Mostly due to its capability in delivering the accurate result with only a few training samples, thing that is being serious matter for SVM family in supervised classification (e.g. Multilayer Neural Network). Works on SVM in remote sensing can be found in numerous literatures. Ref [2] for instance, provide the reviews of the SVM in remote sensing based on the recently (<10 years) published articles in the top remote sensing journals. In addition, another review on the SVM processing methodologies for specific imagery type is given in [3].

Although SVM is a newcomer among the other classifiers (e.g. Maximum likelihood, decision trees, neural network families), it delivers the remarkably comparable and even better result as compared to the forerunners. The SVM superiority has been investigated comprehensively to compare with the maximum likelihood, ANN, and decision tree classifiers, and it is found that SVM gives more stable overall accuracies [4]. Furthermore, it is concluded that as compared to ANN, SVM achieves higher level of accuracy and applicable in even smaller training datasets and high dimensional data [5]. Potential and superiority of SVM in remote sensing are also discussed deeply in ref [6-9]. In the other recent literatures, SVM has been applied to solve various problems related to remote



sensing. For example, monitoring of biophysical parameters [10-12], vegetation classification [13-15], road extraction [16-18], and landmine detection [19].

The SVM popularity motivates the author to further investigate the potential of SVM for object detection as the specific part of the object classification and characterization. This study, utilizes SVM in its simplest and original form, a binary two class classifier [20], to classify the "object" and the "background". Simply, SVM is exploited to extract the object from its background where the resulting outcome is input for further characterization (e.g. area or fractional estimation). In this paper, a brief overview and some mathematical aspects of the SVM are outlined. Then algorithm testing for the synthetic computer-generated geometric image is presented. Here, the algorithm performance over then noisy data is described. Application of the SVM for detection of island vegetation, lake water body, and oil seepage is outlined in the discussion.

2. The SVM: Concepts and Mathematical Insight

SVM typically belongs to family of supervised classifier. It requires training samples given by its supervisor (user). Unlike artificial neural network (ANN), it is less sensitive to the size and number of the training data. Originally, SVM was developed as the binary classifier where it assigns only two possible label; -1 and 1 into a given test sample. Principally, the training algorithm aims to build the separating hyperplane (e.g. decision boundary) based on the properties of the training samples (or specifically, their distribution over the feature space) [20]. In the other words, this hyperplane acts as the separator between the two classes of the samples. Illustration of the hyperplane is depicted in figure 1. The algorithm works by basically, maximizing the margin width of the separating hyperplane (between class -1 and 1) thus the maximum distance between the classes is to be optimized. In the building of the hyperplane, not necessarily all the samples are contributing, but only a subset of them that are chosen as the support vector.

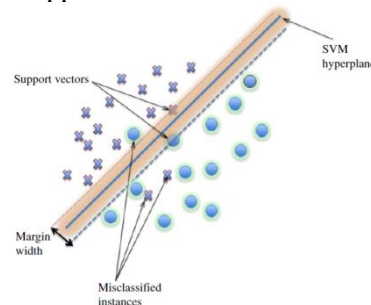


Figure 1. Hyperplane in SVM
(adapted from ref[2])

Since SVM's basic form as the binary classifier is utilized in this study, only mathematical description of the linearly separable case that is outlined. Discussion on its extension is subject for the further research and beyond the scope of this study. However, the interested reader may consult to ref [20]. For two linearly separable classes, the training data can be represented as,

$$\{\mathbf{x}_i, y_i\}, i = 1, \dots, N, y_i \in \{-1, 1\}, \mathbf{x}_i \in R^d \quad (1)$$

where, \mathbf{x}_i denotes the image features and y_i is the label of the information class, that is either +1 for first class and -1 for second class. The hyperplane can be expressed as,

$$\mathbf{W}^T \mathbf{X} + b = 0 \quad (2)$$

\mathbf{X} is the point on the hyperplane, \mathbf{W} is the normal vector to hyperplane, and b is the bias.

Suppose that these conditions are satisfied,

$$\mathbf{W}^T \mathbf{X} + b \geq +1, \text{ for } y_i = +1 \quad (3)$$

$$\mathbf{W}^T \mathbf{X} + b \leq -1, \text{ for } y_i = -1 \quad (4)$$

In combination they read,

$$y_i(\mathbf{W}^T \times \mathbf{X} + b) - 1 \geq 0 \quad (5)$$

Then two hyperplanes can be constructed that is $\mathbf{W}^T \times \mathbf{X} + b = -1$ and $\mathbf{W}^T \times \mathbf{X} + b = 1$ where the margin between the two is $\frac{2}{\|\mathbf{W}\|}$. Now, the task is to maximize this margin, that is by finding

$$\min \left\{ \frac{\|\mathbf{W}\|^2}{2} \right\} \quad (6)$$

Using the Lagrangian formulation to get,

$$L_p = \frac{1}{2} \|\mathbf{W}\|^2 - \sum_{i=1}^n \alpha_i (y_i(\mathbf{W} \times \mathbf{X}_i + b) - 1) + \sum_{i=1}^n \alpha_i \quad (7)$$

where, α is the Lagrange multiplier. Here, L_p is to be minimized with respect to \mathbf{W} and b . This read,

$$\frac{\partial L_p}{\partial b} = 0 \rightarrow \sum_{i=1}^n \alpha_i y_i = 0 \quad (8)$$

$$\frac{\partial L_p}{\partial \mathbf{W}} = 0 \rightarrow \mathbf{W} = \sum_{i=1}^n \alpha_i y_i \mathbf{X}_i \quad (9)$$

Substituting equation (8) and (9) to equation (7) to get,

$$L_d = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \alpha_i \alpha_j y_i y_j \mathbf{X}_i \mathbf{X}_j \quad (10)$$

Now the training is attempting to maximize the last equation with respect to $\alpha_i \geq 0$. Here, the support vectors are all points with $\alpha_i \geq 0$. Recalling back, the solution for \mathbf{W} and b are,

$$\mathbf{W} = \sum_{i=1}^{nsv} \alpha_i y_i \mathbf{X}_i \quad (11)$$

$$b = -\frac{1}{2} (\mathbf{X}_r + \mathbf{X}_s) \quad (12)$$

where, nsv denotes the number of support vectors, \mathbf{X}_r is the support vectors belong to class $y_r=1$ and \mathbf{X}_s is the support vectors belong to class $y_s=-1$.

3. Methodology

In this study, SVM algorithm is performed on MATLAB environment with the aid of the LIBSVM package [21]. For giving the training, sample selection (by polygon cropping) is performed either for the area belongs to object and area belongs to background. The algorithm converts the original RGB image which is 3D array matrix, into binary 2D matrix. It constructs the hyperplane based on the RGB pattern of the training data. The constructing hyperplane is then categorizing the pixel to be in the class of object, thus labeled 1 or in the class background, labeled -1. The emphasize of this study is to seek the minimum size and number of the given training data delivering acceptable outcomes. Thus experiment is undertaken for test images with the condition of containing noise and noise free.

4. Result and Discussion

4.1. Test Image

For testing, computer-generated synthetic image is used (figure 2a). Based on the colour, the image is containing six different objects on which the SVM algorithm is attempting to detect the brown coloured object (e.g. star like objects and worm-like object) and label them 1. Meanwhile, the remaining object are regarded as the background and labelled -1. The standard Gaussian noise is introduced in the test image to investigate the algorithm capability. Training selection is performed by polygon cropping either for object and background (see polygons in figure 2a)

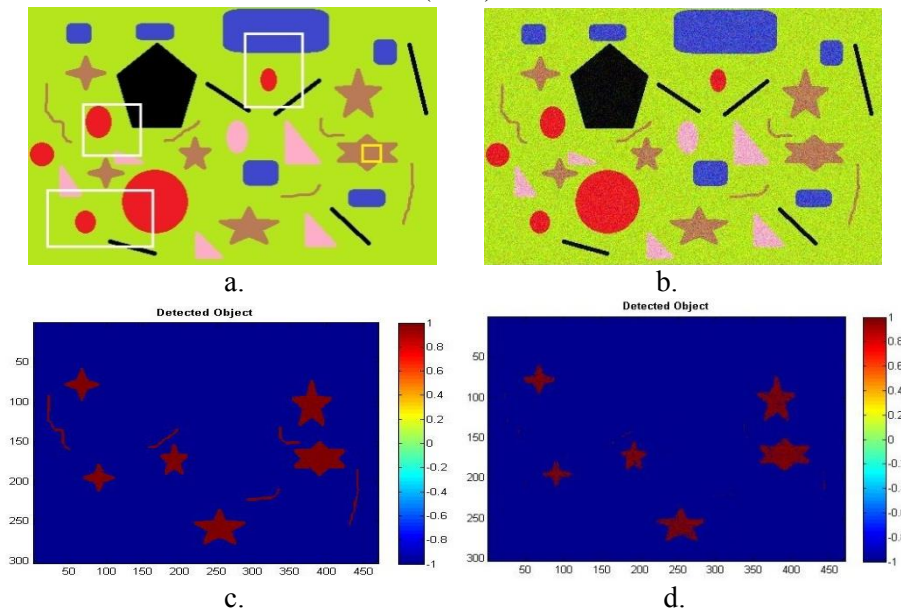


Figure 2. a) Training selection for noise-free synthetic image where 1 yellow polygon is for object and 3 white polygons are for background, b). Gaussian-noised synthetic image. Detection result for the c). noise-free image, and d). noised image

Using the selection of object and background with combination 1:3, the algorithm gives the accurate result for the noise-free image where all the brown objects are successfully labelled 1 and background -1 (see the bar). In contrary, objects in the noised image are not completely detected. The worm-like object is detected as the background instead of object and some stars are not smoothly drawn, indicating that some pixels within stars are labelled -1 instead of 1. This is particularly driven by the presence of noise that distorts significantly the pixel value within the object, makes the classification is more difficult by using the same number of training data. The further experiment on this indicates that with the same selection size, the worm like objects are fully able to detect with combination of training selection is 4:4. However, the unsmooth labelling within stars objects are still observed but significantly reduced.

4.2. Implementation on Remote Sensing Data

Having successfully tested on synthetic image, the algorithm is then implemented to perform object detection from the remotely sensed data taken from several sources. The size of training selection is the same as applied in the synthetic image. Meanwhile, the number of training selection is following the combination of 2:4 for object and background. This is for ensuring that if at least two distinct features are representing object, their information are all incorporated for optimizing the training process.

4.2.1. Vegetation Detection on an Island

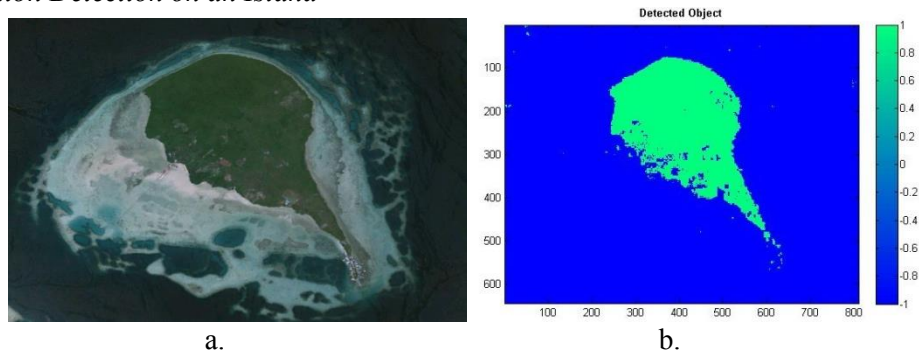


Figure 3. a) An island situated in eastern part of Sabah (taken from Google EarthTM), and b). The detected green object associated with vegetation, the estimated area 13.76%.

4.2.2. Lake Water Body Detection

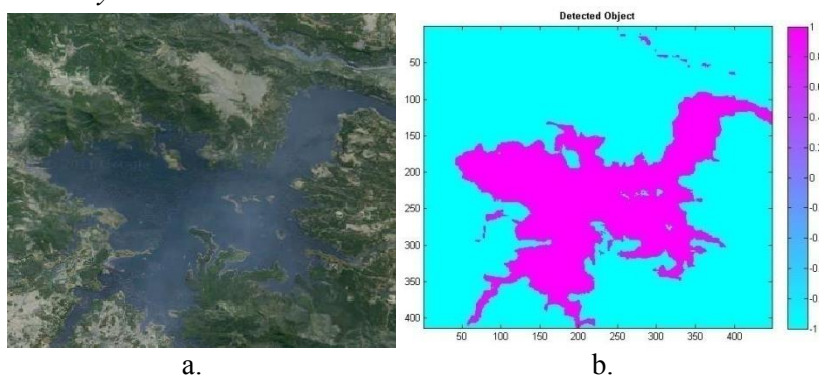


Figure 4. a) Lake Cirata, Purwakarta, West Java, Indonesia (taken from google EarthTM), and b). The detected water body with the estimated area 28.93%

4.3.3. Oil Seepage Detection

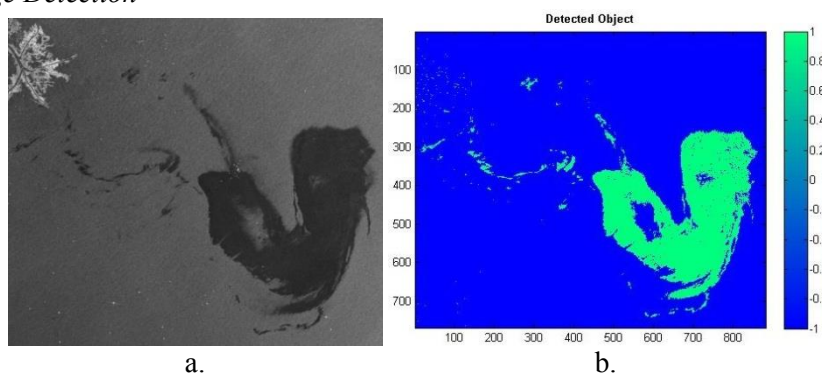


Figure 5. Radar image of Gulf of Mexico Oil Spill, acquired in May 10th 2010 (from USGS), b). Detected oil spill body with the estimated area 14.19%

5. Conclusion

SVM has been used as the binary classifier for detecting object and extracting it from its background. With the limited training data in the algorithm is able to construct the optimum separating hyperplane which minimize the miss classification. From the testing with the synthetic image, it is found that with only 1 selection for object and 3 selection for background, the algorithm can fully detect and extract the desired object. However, in case of noise is present using 4:4 selection is then sufficient for resolving all the objects. The algorithm implementation in the remotely sensed data shows the acceptable result with less error observed.

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