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Impacts of Noise on the Accuracy of Hyperspectral Image Classification by SVM

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Abstract. The support vector machine (SVM) has become a popular tool for image classification recently. The performance of SVM for hyperspectral image classification has been examined from a range of perspectives, but the impacts of noise, errors and uncertainties have attracted less attention. This paper aims to evaluate the impacts of noise on SVM classification. The research is undertaken using real imagery acquired by the OMIS hyperspectral sensor. To assess the sensitivity and reduction capacity of SVM classifier to different types of noise a simulation study is undertaken using two types of noise. The first type of noise is striping, in which some rows or columns of the image have markedly abnormal signals. The second type of noise is caused by some uncertain factors that may impact upon one band, one pixel or one line. This noise may be evaluated by introducing salt and pepper noise. A variety of datasets containing different types of noise are generated and classified using a SVM. The results of the classifications, with particular regard to their accuracy, are compared against a classification of the original dataset and comparative analyses obtained using traditional classifiers including the spectral angle mapper (SAM) and binary encoding (BE). The results indicate that the SVM is more effective to alleviate the effects of noise than SAM and BE.

Keywords: support vector machine (SVM), hyperspectral remote sensing, classification, noise.

1. Introduction

Support vector machine (SVM), which is based on statistical learning theory and structural risk minimization criteria, has been applied to the classification of multispectral and hyperspectral images effectively. The technique is independent of the dimensionality of feature space as the main idea behind this classification technique is to separate the classes with a surface that maximise the margin between them, using boundary pixels to create the decision surface. The data points that are closest to the hyperplane are termed "support vectors". The number of support vectors is thus small as they are only those points close to the class boundaries [1-3]. The SVM has considerable attractions for the classification of hyperspectral remote sensing imagery as it is reported to be suitable for application to high-dimensional data sets, robust to noise and uncertainty, and capable of accurate classification for small training samples. Lots of studies have been done on remote sensing image classification using SVM [2-9]. The performance of SVM for hyperspectral data classification has been examined from a range of perspectives, notably those linked to feature dimensionality, sample size and generalization ability, but the impacts of noise, errors and uncertainties have attracted less attention, so they are chosen as the topic of this paper.

Any remote sensing images are corrupted by different types and amounts noises. The noises come mainly from data capture and transmission process. Image sensor is influenced by various factors during working process, such as environmental conditions and the quality of the sensor components. The data in the process of transmission is contaminated by noise due to the interference of transmission channel. Two common types of noise are stripping noise and salt and pepper noise. Sometimes a detector does not fail

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completely, but simply goes out of radiometric adjustment. The result would be an image with systematic, noticeable lines that are brighter than adjacent lines. This is referred to as stripping [15]. Salt and pepper noise is a common model for the effects of bit errors in transmission, malfunctioning pixels and faulty memory location [13, 16].The noises greatly reduce the utilization of data. Therefore, much work has been done on removing noise [10-14].This paper aims to evaluate the impacts of noise on SVM classification and compare SVM's alleviation ability to noise with other traditional classifiers.

2. Theory

Support vector machine (SVM) consists in finding the optimal separation surface between classes thanks to the identification of the most representative training samples of the side of the class. These samples are called support vectors [1, 2]. If the training data set is not linearly separable, the kernel method is used to simulate a non-linear projection of the data in a higher dimension space [1-3].

In the two-class case, a support vector classifier attempts to locate a hyperplane that maximises the distance from the members of each class to the optimal hyperplane[3]. We assumed that N training samples are represented by $\{(x_i, y_i), i = 1,2,3..., N\}$, with x∈Rn, y∈±1. The hyperplane is defined by $w \cdot x = b$ where (w, b) are the parameters of the hyperplane. The vectors that are not on this hyperplane lead to: $w \cdot x + b \neq 0$ and allow the classifier to be defined as: $f(x,\alpha) = \mathrm{sgn}(w \cdot x + b)$ [2]. The hyperplane for which the distance to the closest point is maximal is called the optimal separating hyperplane(OSH) [1,3].The support vectors lie on two hyperplanes, which are parallel to the optimal hyperplane, of equation: $w \cdot x + b = \pm 1$.

The maximization of the margin with the equations of the two support vector hyperplanes leads to the following constrained optimization problem [1]:

$$\min \ \{\frac{1}{2} \| w \|^2\} \text{ with } y_i(w \cdot x + b) \geq 1, i = 1,..., N. \tag{1}$$

If the training samples are not linearly separable, a regularization parameter C and error variables $\xi_i \geq 0$ are introduced in (1) in order to reduce the weightening of misclassified vectors [2, 3, 5].So (1) can be written as :

$$\min\{\frac{1}{2} \| w \|^2 + C\sum_i \xi_i\} \text{ with } y_i(w \cdot x_i + b) - 1 + \xi_i \geq 0 \tag{2}$$

This optimization problem can be solved using Lagrange multipliers and then becomes: [1]

$$\begin{cases} \min\left\{\sum_{i=1}^{N} \lambda_i - \frac{1}{2}\sum_{i,j=1}^{N} \lambda_i \lambda_j y_i y_j x_i \cdot x_j\right\}, \\ 0 \leq \lambda_i \leq C, \forall i = 1,2,..., N, \\ \sum_{i=1}^{N} \lambda_i y_i = 0, \forall i = 1,2,..., N, \end{cases} \tag{3}$$

Where the λ_i are the Lagrangian multipliers and are nonzero only for the support vectors.

To reduce computational demands in feature space, it is convenient to introduce the concept of the kernel function K such that [1,3,6]:

$$K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j) \tag{4}$$

Then, the kernel function is computed in place of computing dot products $(x_i \cdot x_j)$ in equation (3), which could be computationally expensive [2]. A number of kernel functions are used for support vector classifier. Details of some kernel functions and their parameters used with SVM classifiers are discussed by Vapnik [1, 3].

SVM are initially designed to two-class problems. When dealing with multiple classes, an appropriate multi-class method is needed. There are two types of approaches for multi-class SVM usually [4]. One is by constructing and combining several binary classifiers. The other is by directly considering all data in one optimization formulation. A number of methods are suggested in literature to create multi-class classifiers using two-class methods [3, 4]. “One against one method” is used popularly, in which $M(M-1)/2$ classifiers are applied on each pair of classes.

3. Experiments and analysis

3.1. Data

The experiment data is the OMIS hyperspectral image captured using the sensor produced by CAS, and the latitude and longitude are 40° 11'25.94"N and 116° 18'56.97"E. The image has 512 rows, 536 pixels and 64 bands. There are some bad bands, so only 53 bands are selected. Figure 1 (a) is the RBG composite image of the hyperspectral image (R: Band 18 with wavelength of 0.6639 μm, G: Band 9 with wavelength of 0.5531 μm, and B: Band 3 with wavelength of 0.4773 μm). In Figure 1(a), the green region is grass land, the black region stands for fish pond region, the yellow region is the yellow grass, and the white region is the inhabited area.

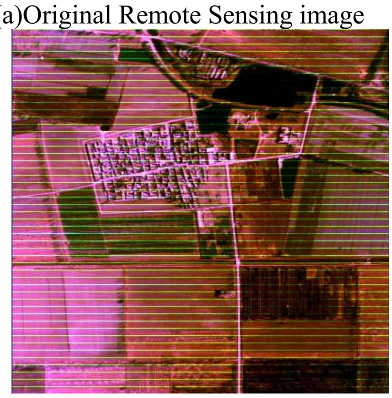
To assess the sensitivity and reduction capacity of SVM classification to different types of noise a simulation study is undertaken using various noises. These noises are added into 50% of the bands.

The first type of noise is stripping. The striping noise may occur in one or more of the bands sensed. The maladjusted line contains valuable information but should be corrected to use. A stripping is added into the original image every eight lines, and the width of each stripping is one pixel. In Figure 1(c) the band 9 is corrupted by stripping noise.

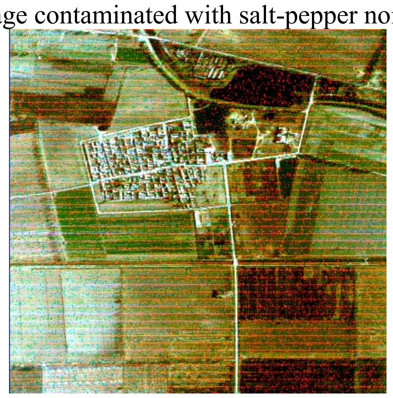
The second type of noise is so-called salt and pepper noise. This is caused by some uncertain factors. They are introduced to some bands so that both the specific bands and the spectral signature of some pixels are changed. Image is corrupted by salt and pepper noise which means a noisy pixel has a high value due to positive impulse noise, or has a low value due to a negative impulse noise [12]. The salt and pepper noise with probabilities 0.1 are added into the original dataset. In Figure 1(b) band 18 and 9 are corrupted by salt-pepper noise.

(a)Original Remote Sensing image

(b) image contaminated with salt-pepper noise



(c) image contaminated with stripping noise



(d) image contaminated with stripping and salt-pepper noise

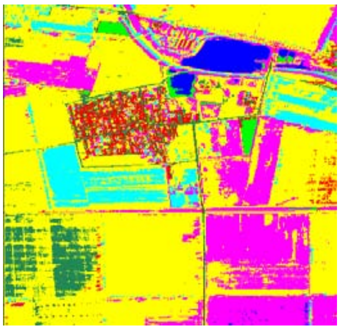
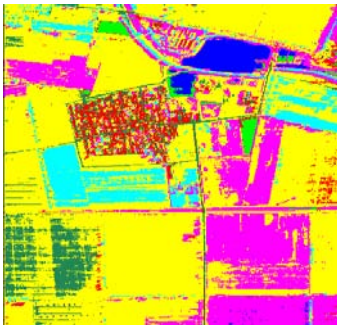
Fig. 1: Original and simulated image with noises

Some bands are corrupted by stripping noise and salt-pepper noise simultaneously. Those bands can be called “bad band” because the spectral information is destroyed seriously. In Figure 1(c) the band 18 is corrupted by stripping noise and salt-pepper noise.

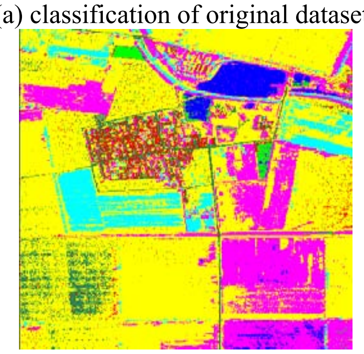
3.2. Results and Discussions

According to ground truth data and previous field work, the classification involves the identification of seven land cover types (water, crop land, grass land, yellow grass, inhabited area, road and bare soil) from the OMIS hyperspectral image.

Figure 2 are the results of SVM classification to the simulated images contaminated with stripping; salt-pepper noise and mixed noise and the accuracy are listed in Table 1. In order to compare the effectiveness of alleviating effects of noise, original dataset are classified using SVM too.

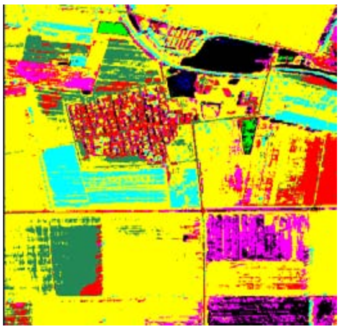
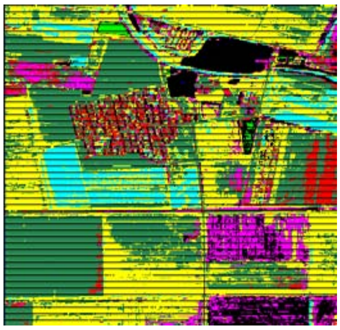



(a) classification of original dataset (b) classification of dataset with stripping noise

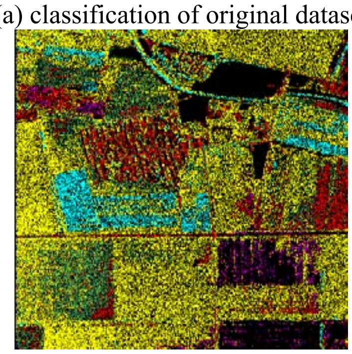
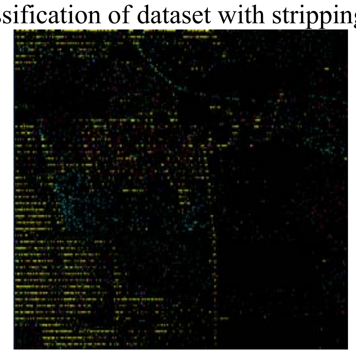



(c) classification of dataset with salt-pepper noise (d) classification of dataset with mixed noises

Fig. 2: classification results of different dataset using SVM

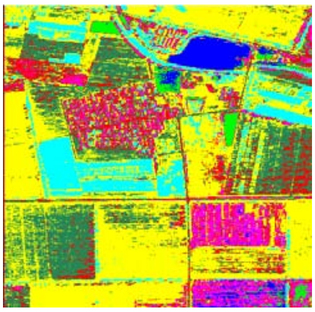



(a) classification of original dataset (b) classification of dataset with stripping noise

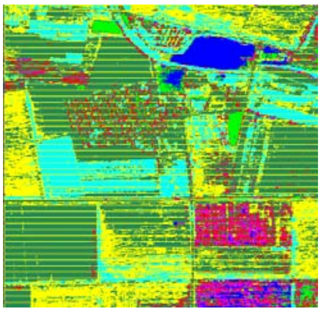



(c) classification of dataset with salt-pepper noise (d) classification of dataset with mixed noise

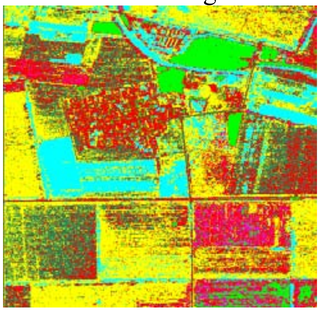
Fig. 3: classification results of different dataset using SAM



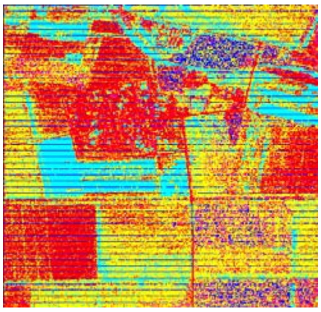
(a) classification of original dataset



(b) classification of dataset with stripping noise



(c) classification of dataset with salt-pepper noise



(d) classification of dataset with mixed noise

Fig. 4: classification results of different dataset using Binary Encoding

Table 1 Accuracy statistics of different classifiers of different dataset.

Dataset	SAM		BE		SVM	
	Overall accuracy	Kappa	Overall accuracy	Kappa	Overall accuracy	Kappa
Original image	49.8612%	0.4382	68.1776%	0.6281	82.7012%	0.7974
Image with stripping noise	43.5708%	0.3812	62.3497%	0.5608	82.4237%	0.7941
Image with salt and pepper noise	22.7567%	0.1812	48.0111%	0.3979	79.5560%	0.7603
Image with mixed noises	2.1277%	0.0141	35.9852%	0.2466	77.7058%	0.7387

The results of the classifications, with particular regard to their accuracy, are first compared against the classification of the original dataset, and then comparative analyses are obtained using traditional classifiers including the Spectral Angle Mapper (SAM) and Binary Encoding (BE). The impact of salt and pepper noise on SAM classification is quite serious. When the dataset is contaminated with "bad band", the SAM classification is so poor that the ground object can't be identified. Figure 3 and 4 demonstrate the classification results of SAM and BE, and their accuracy statistics are listed in the Table 1.

Based on the statistical results in Table 1, some primary conclusions can be derived. Firstly, SVM classifier outperforms traditional SAM and BE classifiers for any imagery. The classification accuracy of SVM to original data is higher than SAM and BE. Secondly, SVM can perform better than SAM and BE when the image is contaminated with different types of noises. When stripping noise exists, the Kappa coefficient of SVM classification is 0.7941, but the Kappa coefficient of SAM and BE classification are 0.3812 and 0.5608. As for salt and pepper noise, the Kappa coefficient of SVM classification declines a little by 0.0371, but the Kappa coefficients of SAM and BE classification decline by 0.2570 and 0.2302. Even if the dataset contains "bad bands", the Kappa coefficient of SVM classification just decreases by 0.0587. Thirdly, as regards the two types of noise, the impact of salt and pepper noise on classification accuracy is stronger than stripping noise on classification accuracy. Therefore, it is important to remove salt and pepper noise [12-14]. Fourthly, the more the dataset is contaminated with noise, the worse the classification result is.

It can be found as well, when the data set is contaminated with noise, the accuracy of SVM classification decreases a little, however, the accuracy of traditional classifiers including SAM and BE decrease greatly. So it can be concluded that SVM is more effective to alleviate the effects of noise than SAM and BE.

4. Conclusions

Hyperspectral remote sensing information is becoming more and more popular and significant owing to its advantages such as fine spectral description, detailed signature record and potential feature discovery. Since traditional remote sensing image classifiers are not so effective for hyperspectral data, much research effort has been devoted to analysis of the performance of support vector machine (SVM) in hyperspectral image classification, which are proved to be better than traditional classifier.

In order to assess the sensitivity and reduction capacity of SVM classification to different types of noises, the hyperspectral image is corrupted by two types of noises. The SVM classification accuracy to noisy images, compared with the SVM classification of original image, reduces a little. Therefore, it indicates that the impact of noise on the accuracy of hyperspectral image classification by SVM is obvious but limited. Besides, in order to evaluate the impacts of noises on the accuracy of different classifiers, comparative analyses are conducted when SAM and BE are used. The accuracy of the SVM, SAM and BE classifications derived from each data set are compared. The results indicate that the SVM is more effective to alleviate the effects of noise than SAM and BE. This may be another advantage of SVM classifier. Combined with previous SVM advantages, it suggests a conclusion that SVM classifier is an effective classifier to hyperspectral imagery containing noises due to different factors. In this paper, some qualitative analyses are studied, but the quantitative analyses need to be investigated further. The quantitative analysis on the impacts of noise on the accuracy of SVM classification will be studied in the near future.

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