HYBRID SVM AND SVSA METHOD FOR CLASSIFICATION OF REMOTE SENSING IMAGES

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1. INTRODUCTION

Recently, particular attention has been dedicated to support vector machines for the classification of multispectral and hyperspectral remote sensing images [1-2]. A linear support vector machine (LSVM) is based on determining an optimum hyperplane that separates the data into two classes with the maximum margin [3]. The LSVM typically has high classification accuracy for linearly separable data. However, for nonlinearly separable data, it usually has poor performance. For this type of data, the Support Vector Selection and Adaptation (SVSA) method was developed, but its classification accuracy is not very high for linearly separable data in comparison to LSVM [4]. In this paper, we present a new classifier that combines the LSVM with the SVSA, to be called the Hybrid SVM and SVSA method (HSVSA), for classification of both linearly and nonlinearly separable data and remote sensing images. The experimental results show that the HSVSA has higher classification accuracy than the traditional LSVM, the nonlinear SVM (NSVM) with different types of kernel, and the previous SVSA.

2. SUPPORT VECTOR SELECTION AND ADAPTATION

The method of Support Vector Selection and Adaptation (SVSA) was especially introduced to overcome the drawbacks of the NSVM involved in choosing a proper kernel type with competitive performance [5-6]. The SVSA method has some advantages over the NSVM that requires less computation time compared to NSVM, and no kernels are needed. With nonlinearly separable data, the classification performance of the SVSA is competitive with the NSVM.

The SVSA method consists of two stages: selection of support vectors obtained by the LSVM and adaptation of the selected support vectors. In the selection stage, some of the support vectors are eliminated, as they are not sufficiently useful for classification. In the second stage, the remaining support vectors are adapted with respect to the training data to generate the reference vectors that are subsequently used for classification of testing data. Adaptation is achieved by using a method that is similar to the Learning Vector Quantization algorithm [7].

In terms of classification performance, the SVSA outperforms the LSVM for nonlinearly separable data. It is also competitive with the NSVM in the classification of nonlinearly separable data. Therefore, a nonlinear classification performance can be achieved by the SVSA without the need for a kernel.

3. HYBRID SVM AND SVSA METHOD

The LSVM gives the best classification accuracy for linearly separable data. According to the results obtained with some experiments done with both SVSA and SVM, it was observed that the SVSA as well as the NSVM are not efficient classifiers with linearly separable data in comparison to the linear SVM. In order to increase the classification accuracy of the SVSA for linearly separable data, the hybrid SVM and SVSA (HSVSA) method is introduced in this paper. During the implementation of the SVSA, the results of the linear SVM are also available, and by utilizing this information, the hybrid model is generated by using the results of both LSVM and SVSA.

For this purpose, a separating hyperplane and the reference vectors are first determined by the linear SVM and the SVSA, respectively, with respect to the training data. Afterwards, a validation dataset generated from the training data is classified with respect to the hyperplane and the reference vectors. For the hybrid model, the perpendicular distance from each data to the hyperplane obtained in the previous step is calculated based on the validation set. The region of validation data is decomposed with hyperplanes, which are parallel to the LSVM's hyperplane, into n segments with respect to their distances. The classification accuracy of each method is calculated for the data located in each segment, and the winner classifier having the highest accuracy is determined in each segment. In the classification of testing data, the data lying in each segment are determined by using their perpendicular distances to the separating hyperplane, and they are classified by the winner classifier.

4. APPLICATION TO SYNTHETIC AND REMOTE SENSING IMAGES

In our experiments, different types of synthetic data with different types nonlinearity were generated in order to compare the classification performances of the proposed method, the LSVM, the SVSA and the NSVM with different types of kernel. According to the results obtained by the experiments, the hybrid method has the highest classification accuracy for both linearly and nonlinearly separable data in comparison to the other methods. As a remote sensing application, a post earthquake Quickbird satellite image was used to identify damage patterns in the city of Bam, Iran during the 2003 earthquake. The hybrid method, the LSVM, the SVSA and the NSVM were used for classification of damaged and undamaged buildings. According to the results obtained, the hybrid model gave the best classification accuracy in comparison to all the other methods.

5. CONCLUSIONS

In terms of classification accuracy, the linear SVM is the best method for linearly separable data but not for nonlinearly separable, while the SVSA has the highest classification accuracy for nonlinearly separable data but not for linearly separable data. In order to classify both linearly and nonlinearly separable data with a high classification accuracy, we combined the LSVM and the SVSA and introduced a new method named HSVSA method. The hybrid model was tested with both synthetic data with different types of nonlinearity and a remote sensing image, and satisfactory classification accuracies were obtained in comparison to the LSVM, the SVSA and the NSVM with different kernels.

6. REFERENCES

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