SUPPORT VECTOR SELECTION AND ADAPTATION FOR CLASSIFICATION OF EARTHQUAKE IMAGES

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1. INTRODUCTION

Linear support vector machines are based on determining an optimum hyperplane that separates the data into two classes with the maximum margin [1]. With linearly separable data, support vectors exist at the margin. Classification is performed subsequently not by using the support vectors further, but by using the hyperplane dependent on the Lagrange coefficients.

In order to achieve classification of nonlinearly separable data, it is necessary to transform input data by using a nonlinear kernel function, followed by regular SVM. The resulting system is called nonlinear SVM. The choice of kernel function is quite important in order to increase classification accuracy. However, it is generally hard to decide which kernel type is supposed to be used with respect to the given data, especially if the structure of the data is not known in advance.

In order to overcome the necessity of choosing a kernel type, a new method based on support vector selection and adaptation is introduced. Our aim is to achieve the classification performance of the nonlinear SVM by using only the support vectors of the linear SVM. The support vectors are the most important vectors closest to the decision boundary. By further selecting the support vectors which are most helpful to classification and adapting chosen support vectors to be used as reference vectors for increased classification accuracy, a highly accurate learning system is generated for linear as well as nonlinear classification.

2. SUPPORT VECTOR SELECTION AND ADAPTATION (SVSA)

A new method called support vector selection and adaptation (SVSA) is proposed for classification of damage after an earthquake using satellite images. We used pre and post earthquake satellite images in the city of Bam, Iran to extract the ground truth of the damaged buildings. The SVSA method uses the support vectors obtained from Linear SVM, eliminates some of them for not being sufficiently useful for classification, and adaptively modifies the selected support vectors which are used as reference vectors for classification. In this way, nonlinear classification is achieved without need for a kernel.

2.1. Selection and Adaptation

Let $X = \{(x_1, \bar{x}_1), \ldots, (x_N, \bar{x}_N)\}$ represent the training data with $x_i \in \mathbf{R}^p$ and the class labels $\bar{x}_i \in \{1, \ldots, M\}$. N, M and p denote the number of training samples, the number of classes and the number of features, respectively. After applying the linear SVM to the training data, the support vectors are obtained as follows [2]:

$$S = \left\{(s_i, \bar{s}_i) \middle| (s_i, \bar{s}_i) \in X \quad i = 1, \ldots, k\right\} \tag{1}$$

$$T = \left\{(t_i, \bar{t}_i) \middle| (t_i, \bar{t}_i) \in X \backslash S \quad i = 1, \ldots, N-k\right\} \tag{2}$$

where k is the number of support vectors, S is the set of support vectors with the class labels $\bar{s}$, and T is the set of training data vectors with the class labels $\bar{t}$, excluding the support vectors.

In the selection stage, the support vectors in the set S are classified with respect to the set by using the K-Nearest Neighbor algorithm and the labels of the support vectors are obtained as [3]:

$$\bar{s}_i^p = \left\{\bar{t}_l \;\middle|\; l = \text{arg min}_{1 \leq j \leq N-k} \left\{\|s_i - t_j\|\right\}, \quad i = 1, \ldots, k\right\} \tag{3}$$

where $\bar{s}_i^p$ is the predicted label of the i^{th} support vector. Then, the misclassified support vectors are removed from the set S. The remaining support vectors are called reference vectors and constitute the set R:

$$R = \left\{ (s_i, \bar{s}_i) \middle| (s_i, \bar{s}_i) \in S \quad \text{and} \quad \bar{s}_i^p = \bar{s}_i \quad i = 1, \ldots, k \right\} \tag{4}$$

The aim of the selection process is to select the support vectors which best describe the classes in the training set.

The reference vectors to be used for classification are next adaptively modified based on the training data in a way to increase the distance between neighboring reference vectors with different class labels. The main idea of adaptation is that a reference vector causing a wrong decision should be further away from the current training vector, and the nearest reference vector with the correct class should be closer to the current training vector. Adaptation is achieved by using the Learning Vector Quantization (LVQ) algorithm as described below [4, 5].

The adapted reference vectors are used for classification of the training and testing sets. For this purpose, the KNN method is applied to classify the samples with respect to the reference vectors. The Euclidian distances from the input vector to the reference vectors are calculated, and classification is done based on the majority class of the K nearest reference vectors.

3. APPLICATION TO SYNTHETIC AND EARTHQUAKE DATA

In our experiments, we first generated different types of synthetic data with different types of nonlinearity in order to compare the classification performance of the proposed method with the nonlinear SVM. One of the data was banana-shaped, and the other one was created by using mean vectors and covariance matrices in a way to provide nonlinearity. According to the results obtained by the experiments, if the data was not linearly separable, the SVSA was competitive with the Nonlinear SVM and better than the linear SVM in terms of classification accuracy.

During implementation, the results of the linear SVM are also available. Depending on the data, a hybrid model was also developed by using consensus between the results of the linear SVM and the results of the SVSA. The distributions of the wrong decision made by the linear SVM are usually near the separating hyperplane. In the hybrid model, the SVSA method is more effective for classification of the data near the separating hyperplane, and the linear SVM is effective in the classification of the other data. We obtained comparatively good classification accuracy with the hybrid model with most data.

Pre- and post-earthquake Quickbird satellite images with high resolution (0.6 m) were used to identify damage patterns in the city of Bam, Iran during the 2003 earthquake. The ground truth of damaged and nondamaged buildings was generated by using the pre- and post- earthquake images from the area of interest. The SVSA and the hybrid model were used for the classification of the damaged and nondamaged buildings in comparison to the linear and nonlinear SVM methods. According to the results, the hybrid model gave the best classification accuracy in comparison to all the methods applied in the classification. Moreover, the SVSA was better than the nonlinear SVM in this experiment in terms of classification performance.

4. CONCLUSION

In this paper, we addressed the problem of classification of remote sensing data using support vector selection and adaptation method and hybrid model which are reliable for both linearly separable and not linearly separable data. The SVSA method consists of selection of support vectors which contribute to the classification accuracy and adaptation of them based on the class distributions of the data. As a result, it is shown that the SVSA method gives quite satisfactory classification performance in comparison to the nonlinear SVM for both synthetic data and real data, and it is better than the linear SVM as well.

5. REFERENCES

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