Hyperspectral image classification based on improved few shot learning

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Abstract—Aiming at the problem that hyperspectral image labeling training samples are less likely to be over-fitting, and the network cannot be well constrained during training, this paper adopts few shot learning classification method of reconstruction loss function. This method solves the problems of feature difference within a class and distance between features by constructing a loss function. The algorithm is applied to PaviaU, KSC and Salinas hyperspectral images. The experimental results show a certain effect, and a better performance improvement has been achieved in the image classification task.

INTRODUCTION

Compared with general remote sensing images, hyperspectral images provide much larger subtle spectral features with HSI data[1-3]. The traditional pixel-by-pixel method is extremely susceptible to noise, and the importance of similar feature clustering is often ignored when extracting image features, which reduces the classification accuracy. Chen Y et al. [4] introduced deep learning to hyperspectral image classification for the first time, using an autoencoder to extract the spectral features of hyperspectral images. Compared with machine learning methods, the classification accuracy is significantly improved. However, this method only uses the spectral information of the hyperspectral image and ignores the spatial information. Later, Convolution Neural Network (CNN) was widely used in the feature extraction and classification of hyperspectral images[5-9].

In the process of convolutional neural network training, the cross-entropy loss function iteratively trains network parameters by continuously reducing the error between the output value of the network and the actual value, but it also has its inherent shortcomings. Researchers have proposed a series of improvement measures. For example, adding Center Loss [10] auxiliary loss function to the fully connected layer can effectively reduce the dispersion between classes and increase the distinction between classes to a certain extent. The Center Loss function and the Softmax loss function are combined to form a joint loss function. Although Center Loss can reduce the difference of features within a class, it does not consider the feature distance between classes.

Our paper proposes an improved few shot learning classification algorithm based on reconstruction loss function. To deal with the difference of features within a class and fully consider the issue of feature distance between classes. On the basis of the original loss function in the network, one or more loss functions need to be reconstructed to strengthen the constraints on the network during training.

$$loss = -\frac{1}{n}\sum_{x}[y\ln\hat{y} + (1-y)\ln(1-\hat{y})] \quad (1)$$

$$loss_{noin} = -\frac{1}{n}\sum_{x}[y_{noin}\ln\hat{y}_{noin} + (1-y_{noin})\ln(1-\hat{y}_{noin})] \quad (2)$$

$$loss_{Total} = loss + loss_{in} - loss_{noin} \quad (3)$$

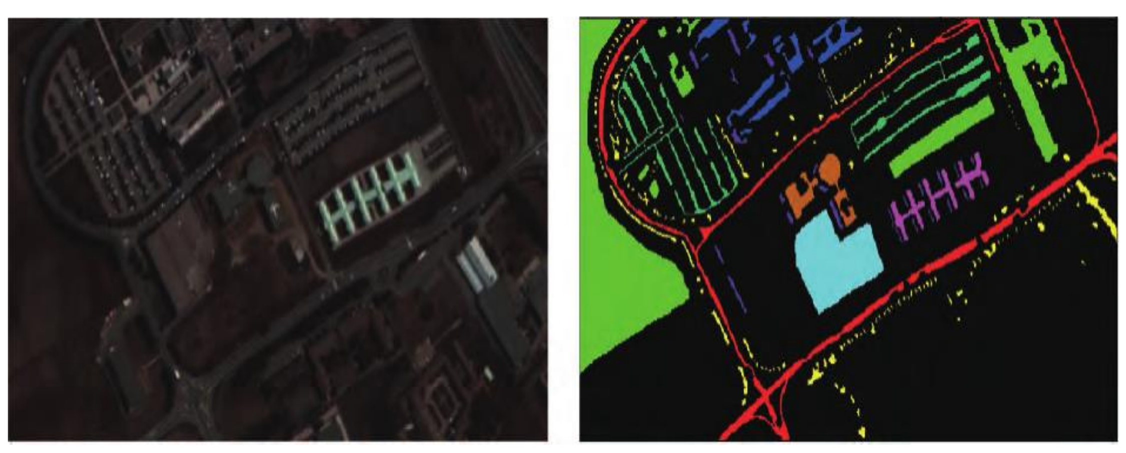

Fig 3. PaviaU remote sensing image

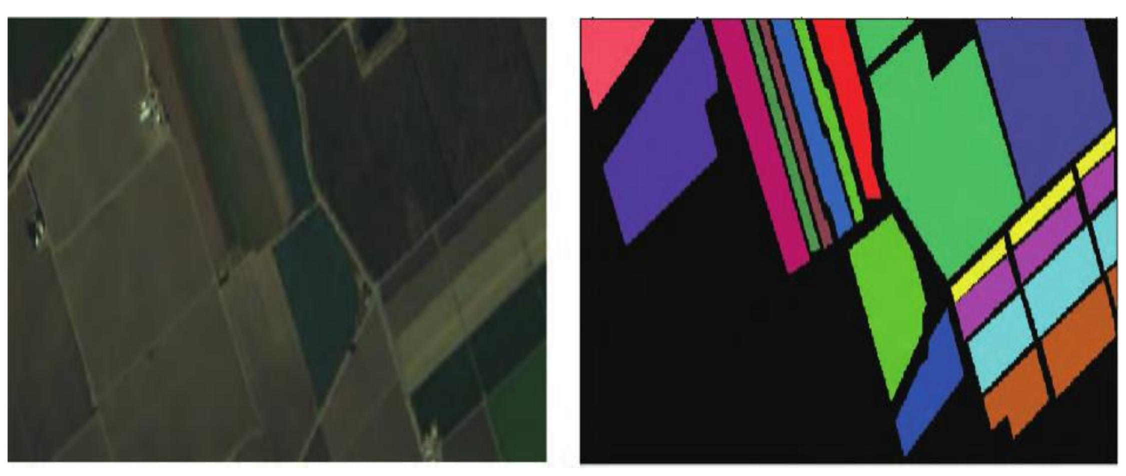

Fig 4. Salinas remote sensing image

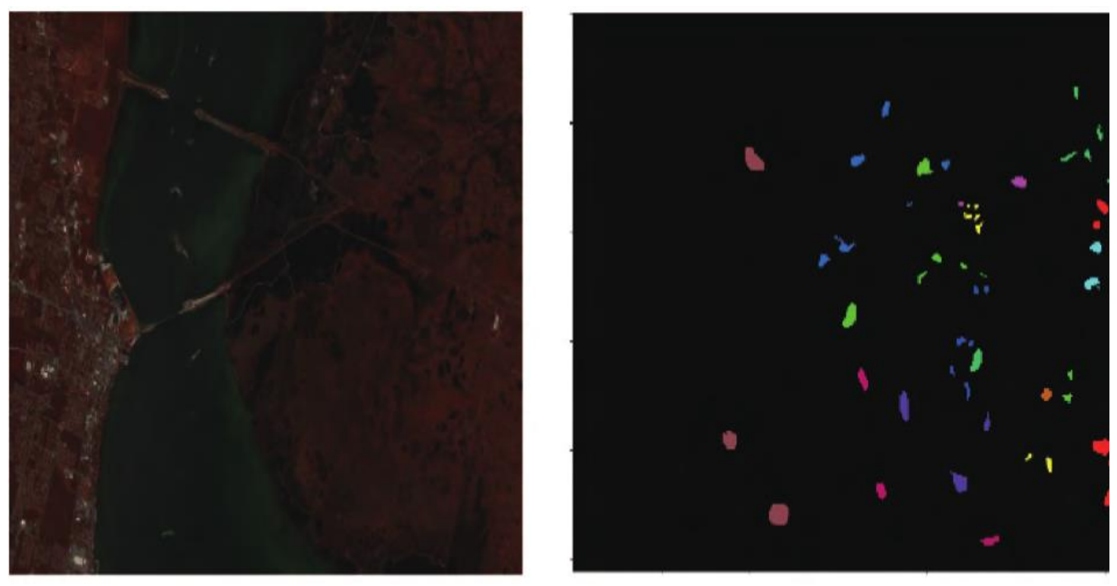

Fig 5. KSC remote sensing image

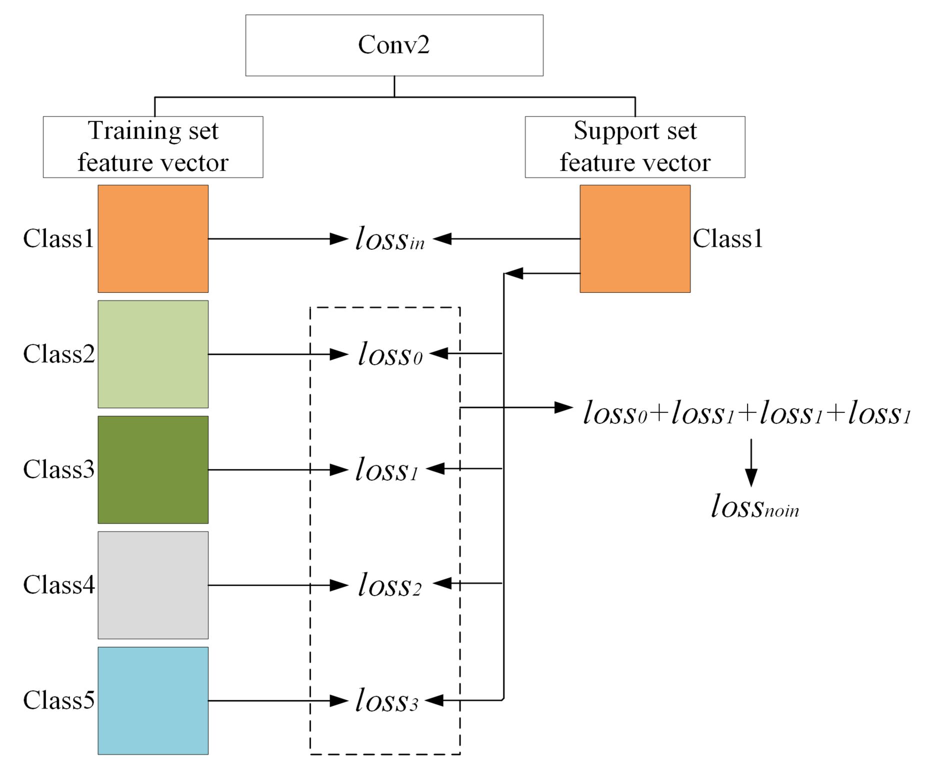

Fig 1. Construct a framework for intra-class and inter-class losses

This paper conducts experiments on the 5-way 1-shot and 5-way 5-shot cases on the hyperspectral image data set. The specific control experiment results are shown in Table I.

TABLE I DATASETS INTRODUCTION

DataSet	Number of categories	Total number of samples	Number of bands	Experiment selection spectrum
PaviaU	9	42776	115	103
Salinas	16	54129	224	204
KSC	13	5211	224	176

In this paper, the relationship network and the improved network are applied to PaviaU, KSC and Salinas hyperspectral images. The specific control experiment results are shown in Table II.

TABLE II AVERAGE TEST ACCURACY BASED ON HYPERSPECTRAL DATASET

Model	PaviaU	KSC	Salinas
Relation Network	86.92%	97.12%	92.54%
Relation Network – L_{noin} (our)	87.88%	97.01%	92.50%

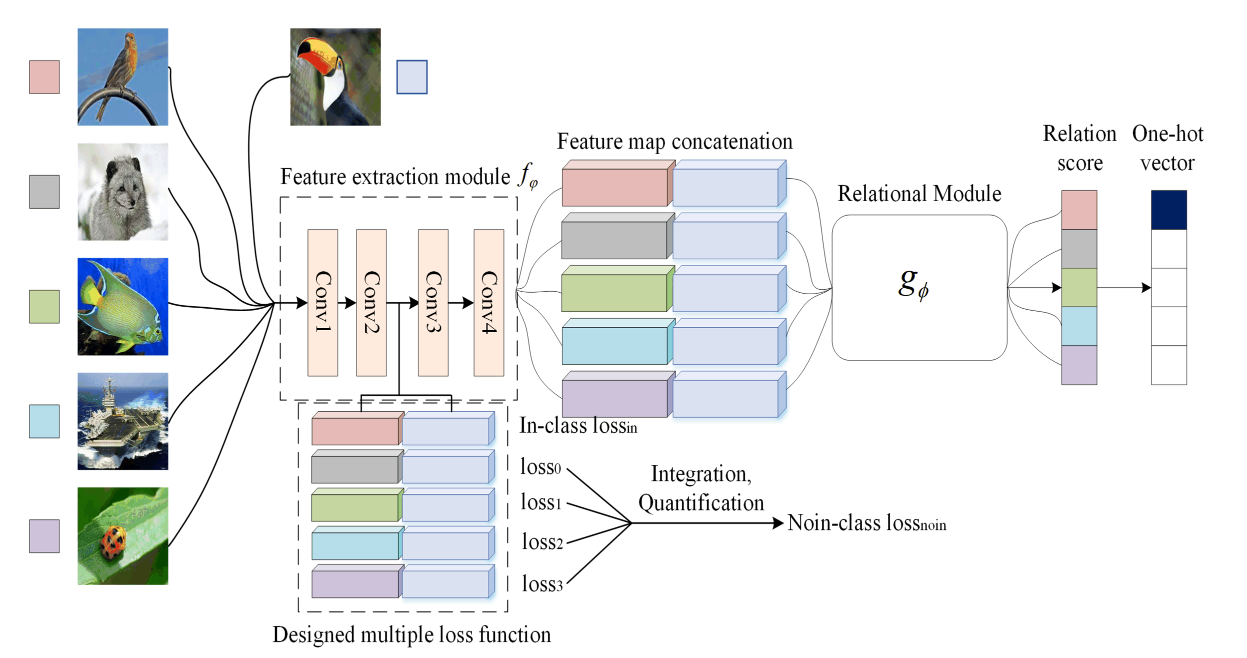

Fig 2. Designed architecture for a 5-way 1-shot problem with one query example.

CONCLUSION

The improved few shot learning classification method proposed in this paper can better deal with the feature difference within the class and fully consider the feature distance between classes. And it can further strengthen the constraints on the model in training. This method shows good classification results on the hyperspectral image data set.