ACTIVE LEARNING BASED AUTOENCODER FOR HYPERSPECTRAL IMAGERY CLASSIFICATION

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ABSTRACT

In this paper, we joint autoencoder with active learning for hyperspectral imagery classification. Specifically, we learn the classifier via autoencoder, where the most informative samples are acitvely selected through the interaction between the autoencoder and active learning. Experimental results, conducted using both the Kennedy Space Center and the Indian Pines hyperspectral images, show that driven by active learning, the performance of autoencoder can be greatly improved.

***Index Terms*—** Autoencoder, hyperspectral imagery classification, active learning, deep learning.

1. INTRODUCTION

Hyperspectral imagery (HSI) contains hundreds of spectral bands so that it can subtly reveal details for the objects on the surface of the Earth [1]. However, the high dimensionality of spectral data also brings difficulties to HSI classification which is deemed as the basic question for the application of remote sensing [2]. Those difficulties have fostered many new classification methodologies, such as support vector machines (SVMs) [3], artificial neural networks (ANNs) [4], multinomial logistic regression [5] (among many others) to improve the performance of classification.

One of the most promising directions is to adopt deep learning (DL) for HSI classification, as which can mine the hidden information contained in the image [6]. DL was first proposed in the artificial intelligence community and has achieved breakthroughs in many fields such as image recognition [7], speech recognition [8] and natural language processing [9]. It simulates the learning procedure of human brain through neural networks. Learning from the multi-layer abstraction mechanism of human brain, the purpose of DL is to realize the abstracting expression of real world objects or data (images, voice and text), and then put the feature extraction and classification/regression in one unified learning framework [6]. Autoencoder, originally introduced for dimensionality reduction, is one of the most useful multi-layer algorithms that can extract deep features of images [10], which is then adopted for HSI classification, leading to promising performance [11, 12]. Although deep learning has many advantages, it has strong requirements regarding the amount of training samples. For example, in the experiments in [11], 60% of the samples in the ground truth image (25500 in 42500) are used for training. This is really a challenge for real scenarios. Therefore, a first concern for deep learning should be how to effectively learn the autoencoders by using limited training samples. A straightforward solution would be increasing the quality of the samples.

In this paper, we develop a new framework for HSI classification that combines autoencoder with active learning strategies. Specifically, we perform active learning to search for the most informative training samples, and then feed them into the autorcoder classifier. Experimental results show that, by taking advantage from active leraning, the autoencoder can obtain much better results by using less training samples.

2. PROPOSED METHOD

Let $\mathcal{S} \equiv \{1, 2, \dots, n\}$ denote a set of integers indexing the training set samples, $\mathcal{C} \equiv \{1, 2, \dots, m\}$ be a set of integers indexing candidate set for active sampling, $\mathcal{K} \equiv \{1, 2, \dots, k\}$ be a set of integers indexing the class of labels, $\mathbf{X} \equiv \{\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots, \mathbf{x}^{(n)}\} \in \mathbb{R}^{n \times d}$ be an image of d-dimensional input feature vectors, $\mathbf{x}^{(i)} \equiv [x_1^{(i)}, x_2^{(i)}, \dots, x_d^{(i)}]^T$ be the input feature vector of pixel i, $L \equiv \{1, 2, \dots, l\}$ be a set of integers indexing the l layer of the neural network, $\boldsymbol{W} \equiv \{\boldsymbol{w}_1, \boldsymbol{w}_2, \dots, \boldsymbol{w}_l\}$ a set of weights and $\boldsymbol{w}_l$ means the weights of layer l. With these notations in mind, the proposed method is illustrated in Fig. 1. The autoencoder classifier consists of pre-training and fine-tuning steps [10]. For the pre-training step, the training samples are active selected [13].

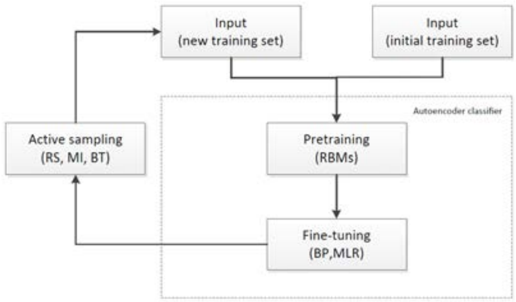


Fig. 1. Flowchart illustrating the proposed method

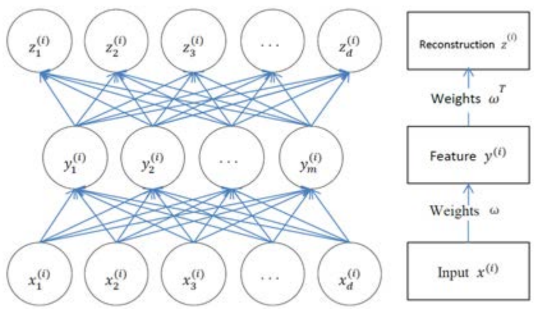


Fig. 2. RBM for pre-training

2.1. Autoencoder

Autoencoder uses the restricted Boltzmann machine (RBM) [10] technique to pre-train the network, and then, the obtained weights are finely tuned via back propagation. In the pre-training phase, as shown in Fig. 2, for a given input vector $\mathbf{x}^{(i)}$ we use the following active function:

$$\mathbf{y}^{(i)} = \frac{1}{1+\exp(-\boldsymbol{w}^T\mathbf{x}^{(i)})}, \tag{1}$$

$$\mathbf{z}^{(i)} = \frac{1}{1+\exp(-\boldsymbol{w}^T\mathbf{y}^{(i)})}, \tag{2}$$

where $\mathbf{y}$ denotes the abstractive feature vectors from input feature vectors $\mathbf{x}$, and $\mathbf{z}$ is the reconstruction of $\mathbf{x}$ through RBM. Therefore, we can obtain the loss function as the cross entropy:

$$\ell(\boldsymbol{w}) = \frac{1}{n}\left[-\sum_{i=1}^{n}\mathbf{x}^{(i)}\log\left(\mathbf{z}^{(i)}\right) - \sum_{i=1}^{n}\left(1-\mathbf{x}^{(i)}\right)\log\left(1-\mathbf{x}^{(i)}\right)\right]. \tag{3}$$

Therefore, the initial weights $\boldsymbol{w}$ can be obtained by minimizing the loss function as follows:

$$\boldsymbol{w} = \arg\min_{\boldsymbol{w}} \quad \ell(\boldsymbol{w}). \tag{4}$$

Fig. 3 illustrates the architecture of the whole autoencoder network and the fine-tuning process. First of all, we use a stack of restricted Boltzmann machines (SRBMs) to learn the new features $\mathbf{y}$, which is the input for the next RBM in the stack. Then, the multinomial logistic regression (MLR) classifier is used to generate the outputs, where we the weights are finely tuned via back-propagation of error derivatives.

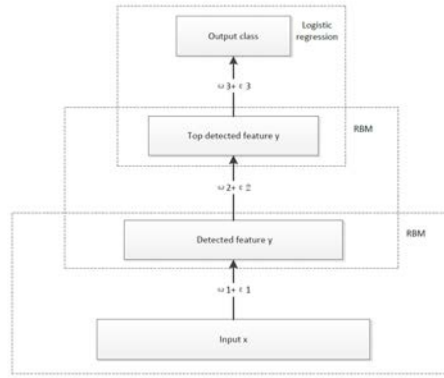


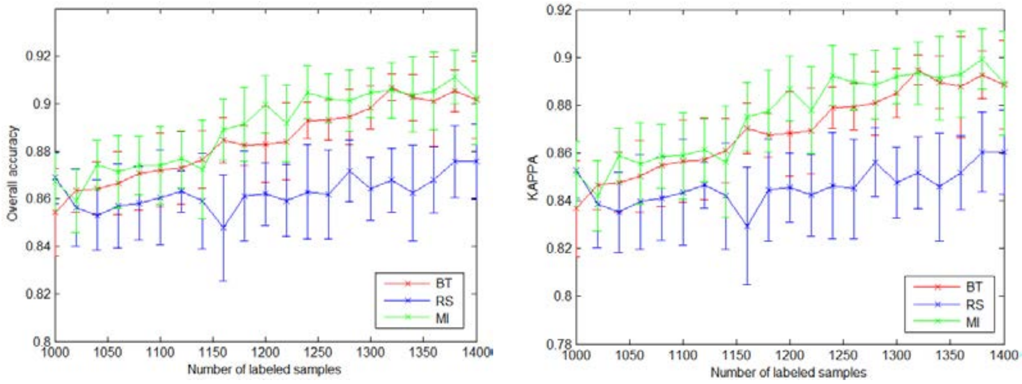
Fig. 3. Fine-tuning of weights using back-propagation algorithm.

2.2. Active Sampling

In this work, in order to promote the performance of autoencoder, we adopt the AL concept from [13–15] to select the most informative training samples, where, two different strategies: Mutual Information (MI) and Breaking Ties (BT) are considered. For comparative purpose, random sampling (RS) is also considered in the experiments.

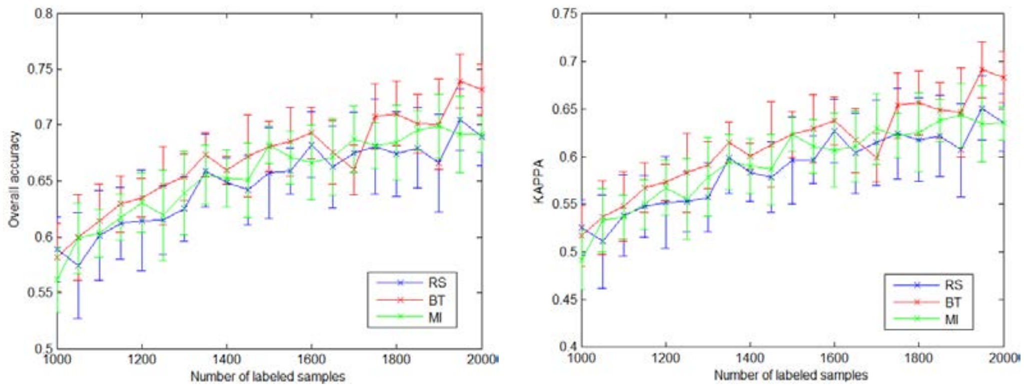
3. EXPERIMENTAL RESULTS

In this section, we evaluate the proposed method using two hyperspectral images, namely, the Kennedy Space Center (KSC) and the Indian Pines dataset. The KSC dataset was acquired by NASA AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) instrument on March 23, 1996. After removed water absorption and low SNR bands, 176 bands were used for the analysis. The Indian Pines dataset was gathered by AVIRIS sensor over the Indian Pines test site in North-western Indiana. Before the analysis, we performed the preprocess which reduce the number of bands to 200 by removing bands covering the region of water absorption, and designated the ground truth into 9 mutually exclusive classes. Figs. 4 and 5 illustrate the obtained OA and kappa statistics as a function of the number of labeled samples for different sampling approaches, respectively using the KSC and the Indian Pines dataset. As can be observed from these two figures, active learning can greatly improve the performance of autoencoder, in comparison with random sampling. For illustrative purposes, Figs. 6 and 7 show the classification maps respectively obtained by using the KSC and the Indian Pines dataset, where the effectiveness of active sampling can be observed.



(a) Overall Accuracy (b) Kappa Coefficient

Fig. 4. Overall Accuracy (a) and Kappa Coefficient (b) with standard deviation as a function of the number of labeled samples for the proposed method using the Kennedy Space Center (KSC) dataset.



(a) Overall Accuracy (b) Kappa Coefficient

Fig. 5. Overall Accuracy (a) and Kappa Coefficient (b) with standard deviation as a function of the number of labeled samples for the proposed method using the Indian Pines dataset.

4. CONCLUSION

In this letter, we have developed an active learning based autoencoder for hyperspectral imagery classification. Specifically, we learn the classifier via autoencoder, from where we using active sampling methods to actively select the most informative samples for training. Experimental results indicate that active learning can greatly improve the performance of autoencoder.

5. ACKNOWLEDGMENTS

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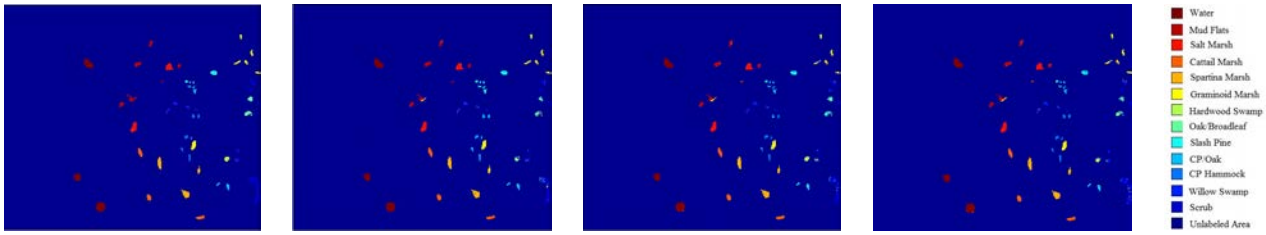
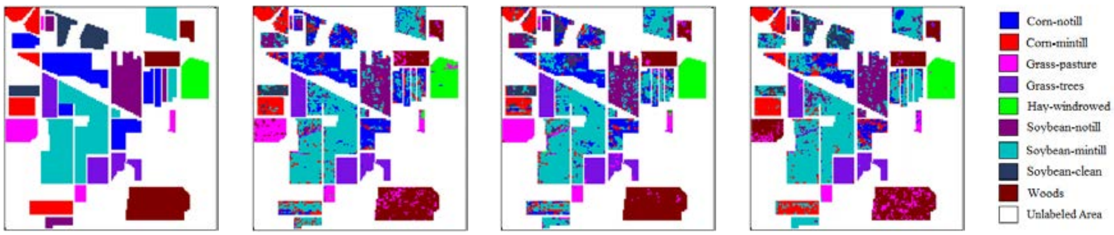


(a) Ground truth (b) BT, OA=90.18% (c) RS, OA=87.56% (d) MI, OA=90.23%

Fig. 6. Classification maps obtained by the proposed active autoencoder approach with Breaking Ties (BT), Random Sampling (RS) and Mutual Information (MI), using the Kennedy Space Center (KSC) dataset.



(a) Ground truth (b) BT, OA=77.05% (c) RS, OA=73.01% (d) MI, OA=75.58%

Fig. 7. Classification maps obtained by the proposed active autoencoder approach with Breaking Ties (BT), Random Sampling (RS) and Mutual Information (MI), using the Indian Pines dataset.

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