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Discriminate Gabor Ensemble Filter using Hyper Spectral Image Categorization

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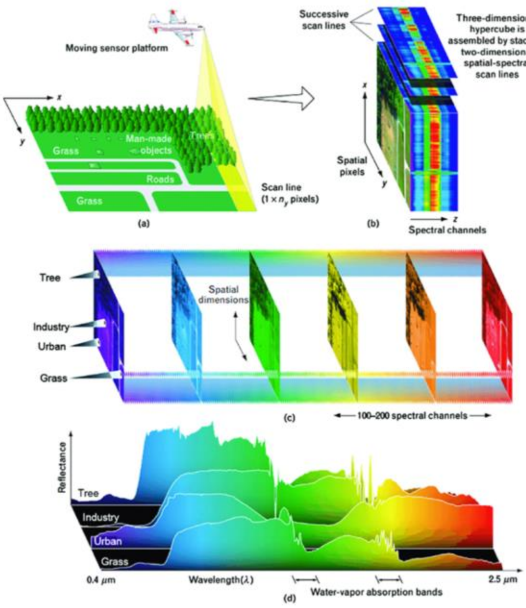
Abstract:
The fixed Gabor filters can extract common features with different scales and orientations, while the learnable filters can learn some complementary features that Gabor filters cannot extract. Based on GEF, we design network architecture for HSI classification, which extracts deep features and can learn from limited training samples. In order to simultaneously learn more discriminative features and an end-to-end system, we propose to introduce the local discriminate structure for cross-entropy loss by combining the triplet hard loss. Results of experiments on three HSI datasets show that the proposed method has significantly higher classification accuracy than other state-of-the-art methods. Moreover, the proposed method is speedy for both training and testing. For a broad range of applications, hyper spectral image (HSI) classification is a hot topic in remote sensing, and convolutional neural network (CNN)-based methods are drawing increasing attention.

However, to train millions of parameters in CNN requires a large number of labeled training samples, which are difficult to collect. A conventional Gabor filter can effectively extract spatial information with different scales and orientations without training, but it may be missing some important discriminative information. In this article, we propose the Gabor ensemble filter (GEF), a new convolutional filter to extract deep features for HSI with fewer trainable parameters. GEF filters each input channel by some fixed Gabor filters and learnable filters simultaneously, and then reduces the dimensions by some learnable 1 × 1 filters to generate the output channels.

Index: Hyper spectral, Image Classification, Gabor Ensemble Filter

I. Introduction:

AHYPERSPECTRAL image (HSI) contains hundreds of continuous bands in the ultraviolet, visible, and infrared regions, which effectively combine spatial and spectral information. HSI classification, that is, classifying every pixel with a certain land-cover type, is the cornerstone of HSI analysis. It has a broad range of applications, including land cover mapping, mineral exploration, water-pollution detection, natural disasters, and biological threats. Many HSI classification algorithms have been proposed over the past decade, including subspace-based methods, support vector machine (SVM), extreme learning machine (ELM), sparse representation classifier (SRC), low rank representation, extended morphological attribute profiles, invariant attribute profiles (IAPs), etc. Deep-learning-based methods have drawn much attention recently in image classification.



International Journal of Engineering, Management and Humanities (IJEMH)
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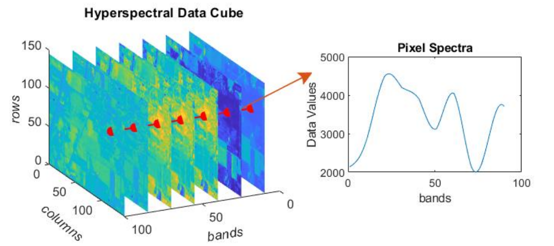
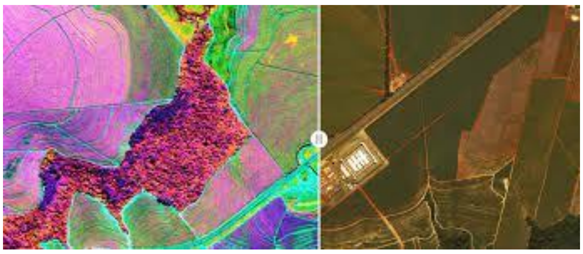
Deep learning uses a neural network with multiple hidden layers to automatically learn features from the original image, layer by layer. Due to its excellent performance, deep learning has been applied to HSI classification, with better results compared to conventional shallow methods.



For HSI, the number of labeled samples is limited, because it takes effort to determine the class of each pixel. Some unsupervised deep-learning methods, including stacked automatic encoder (SAE) and deep brief network (DBN), have been proposed to extract features for HSI. However, since SAE- and DBN-based methods only have 1-D fully connected layers, they cannot automatically learn spatial features. Furthermore, they cannot provide end-to-end classification methods, because they need to use traditional classifiers. Convolution neural networks (CNNs) have excellent image-classification capabilities and provide end-to-end classification methods. Many CNN-based HSI classification methods have been proposed recently. In particular, increased the number of training samples by constructing sample pairs to overcome the problem of insufficient training samples and proposed a CNN with pixelpair features (CNN-PPF) to classify HSI. proposed a diverse region-based CNN (CNN-DR) for HISclassification, where the diverse regions can simultaneously take advantage of spectral, spatial structure, and semantic context-aware information in each pixel.

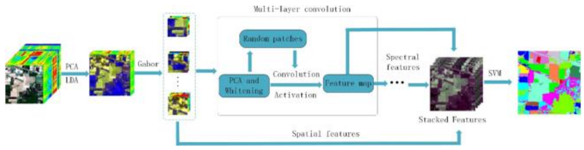


In this article, we propose a new filter, called the Gabor ensemble filter (GEF), to effectively combine the Gabor filters and the standard convolutional filters. Different from the existing methods that use Gabor filters merely for preprocessing and those discarding to train the standard convolutional filters proposed method filters each input channel by fixed Gabor filters together with learnable filters, followed by some learnable filters to obtain the output channels. Based on GEF, we designed network architecture for HSI classification, which can not only extract deep enough features but can be learned by limited training samples.

Because Gabor filters can extract good convolutional features without training processing, and it is hard to obtain Gabor-like filters automatically when training CNN, we are inspired to incorporate Gabor filters and learnable convolutional filters for HSI classification. However, how to effectively combine them is a meaningful issue. Existing methods either used Gabor features as the preprocess step or discarded to train the standard convolutional operator.

The main contributions of this article are as follows.

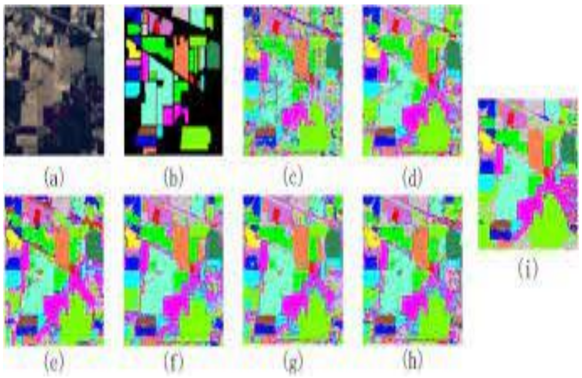
1) We propose a new convolutional operator by combining traditional Gabor filters and learnable filters, so that deep enough features can be extracted by the network with fewer trainable parameters that can be learned by a limited number of training samples. The Gabor filters can extract common features with different scales and orientations, while the learnable filters can learn some complementary features that Gabor filters cannot extract.



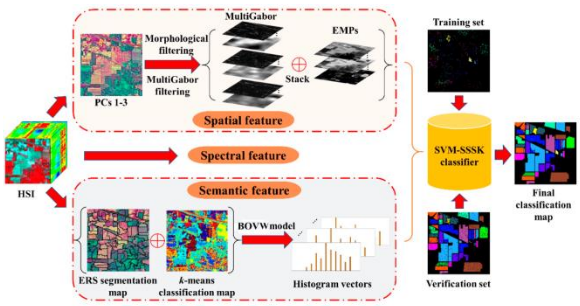
2) We propose to introduce the local discriminant structure for cross-entropy loss by combining the triplet hard loss, so that more discriminative features and an end-to-end system are learned at the same time.

3) With limited training samples, the proposed method performs significantly better than other state-of-the-art HSI classification methods. Moreover, the proposed method is fast for both training and testing.

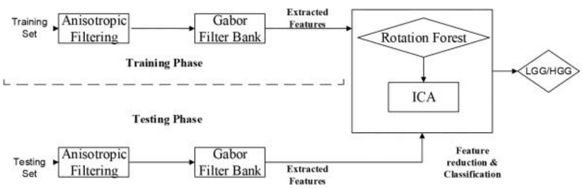
International Journal of Engineering, Management and Humanities (IJEMH)
Volume 4, Issue 5, Sep.-Oct., 2023 pp: 212-218 www.ijemh.com



1) To learn good features for HSI, the depth and the number of parameters of CNN must be sufficiently large. However, because of the limited training samples for HSI, it is easy to over fit if the network is complex. CNNs normally fail to handle large and unknown object transformations when the training data are insufficient. Furthermore, a complex network requires a long training time.
2) Most CNN-based HSI classification methods only use traditional cross-entropy loss to train the network. However, as some samples have similar spectra but different labels, or vice versa, to solely use the cross entropy loss is not good enough to learn discriminative features.
A conventional Gabor filter can effectively extract spatial information with different scales and orientations without training, but it may be missing some important discriminative information.
In this article, we propose the Gabor ensemble filter (GEF), a new convolutional filter to extract deep features for HSI with fewer trainable parameters. GEF filters each input channel by some fixed Gabor filters and learnable filters simultaneously, then reduces the dimensions by some learnable 1 × 1 filters to generate the output channels.

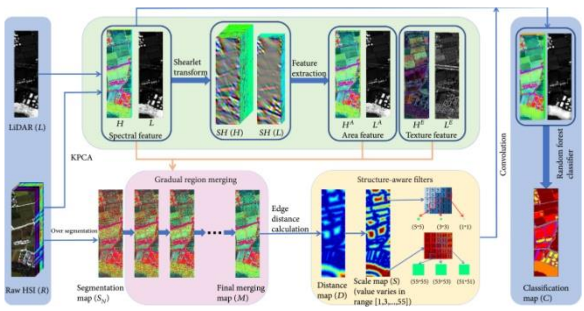


Gabor filters can effectively extract features with different scales and orientations; they may be missing some important discriminative information. On the other hand, because there are limited training samples, it is hard to train a well CNN for HSI classification. Inspired by the aspects, we proposed a new method to effectively combine the standard convolution operator and the Gabor filters, so that deep enough features can be extracted by the network with fewer trainable parameters. Specifically, we first empirically set different parameter values of scales and orientations to generate some fixed Gabor filters. Note that the fixed Gabor filters do not participate any training procedure. Then, we combine the fixed Gabor filters and the learnable filters to extract deep features of HSI. The Gabor filters can extract common features with different scales and orientations, while the learnable filters can capture some complementary features that Gabor filters cannot extract.



Discriminative Learning

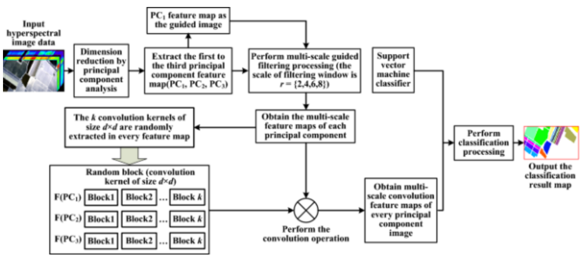
Most existing CNN-based HSI classification methods only used cross-entropy loss to train the network. However, cross-entropy loss is not the best criterion for HSI classification. There are some other loss functions that can learn discriminative features that suppress intraclass variations and maximize the gap between the samples from different classes. In particular, the triplet hard loss can characterize the local discriminative structure, which suppresses the distance between the selected positive pairs and maximizes the gap between the selected negative pairs. However, only using the triplet loss cannot learn an end-to end system. In this article, we propose to combine the triplet hard loss and cross-entropy loss to learn more discriminative features and an end-to-end system at the same time.



International Journal of Engineering, Management and Humanities (IJEMH)
Volume 4, Issue 5, Sep.-Oct., 2023 pp: 212-218 www.ijemh.com

The Gabor filter result contains more useful discriminative features than those of the original HSI. On the other hand, CNNs have achieved impressive results for HSI classification compared with traditional methods. However, it requires a large number of labeled training samples, which are difficult to collect. Because Gabor filters can extract good convolution features without training processing, and it is hard to obtain Gabor-like filters automatically when training CNN, we are inspired to incorporate Gabor filters and learnable convolution filters for HSI classification. However, how to effectively combine them is a meaningful issue.

The triplet hard loss can characterize the local discriminative structure, which suppresses the distance between the selected positive pairs and maximizes the gap between the selected negative pairs. However, only using the triplet loss cannot learn an end-toend system. In this article, we propose to combine the triplet hard loss and cross-entropy loss to learn more discriminative features and an end-to-end system at the same time.

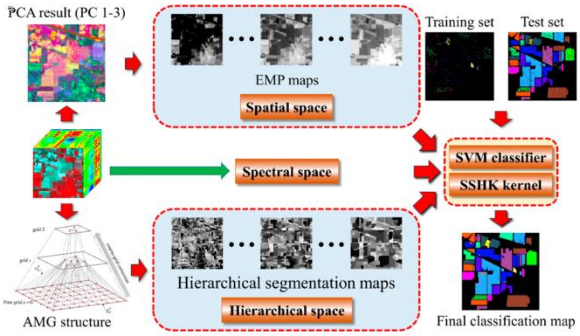


Most CNN-based HSI classification methods only use traditional cross-entropy loss to train the network. However, because some samples have similar spectra but different labels, and vice versa, to only use the cross-entropy loss is not sufficient to learn discriminative features.

Convolutional neural network (CNN)

Hyper spectral image (HSI) classification is a hot topic in remote sensing, and convolutional neural network (CNN)-based methods are drawing increasing attention.

However, to train millions of parameters in CNN requires a large number of labeled training samples, which are difficult to collect. A conventional Gabor filter can effectively extract spatial information with different scales and orientations without training, but it may be missing some important discriminative information.

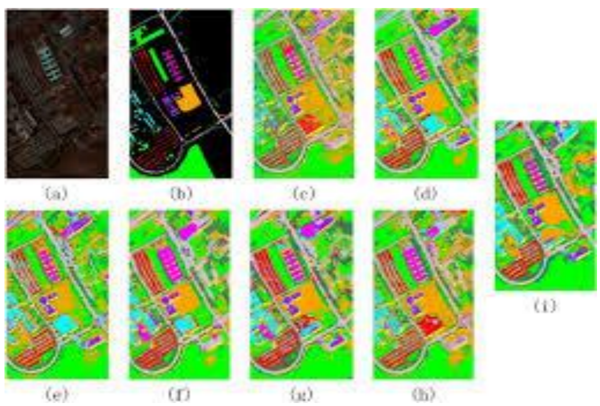


Specifically, we first empirically set different parameter values of scales and orientations to generate some fixed Gabor filters. Note that the fixed Gabor filters do not participate any training procedure.

Then, we combine the fixed Gabor filters and the learnable filters to extract deep features of HSI. The Gabor filters can extract common features with different scales and orientations, while the learnable filters can capture some complementary features that Gabor filters cannot extract.

Discriminant learning

The fixed Gabor filters can extract common features with different scales and orientations, while the learnable filters can learn some complementary features that Gabor filters cannot extract.



Based on GEF, we design a network architecture for HSI classification, which extracts deep features and can learn from limited training samples.
In order to simultaneously learn more discriminative features and an end-to-end system, we propose to introduce the local discriminant structure for cross-entropy loss by combining the triplet hard loss.
However, since SAE- and DBN-based methods only have 1-D fully connected layers, they cannot

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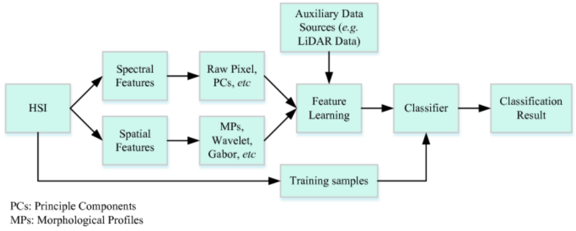
automatically learn spatial features. Furthermore, they cannot provide end-to-end classification methods, because they need to use traditional classifiers.

Gabor filter

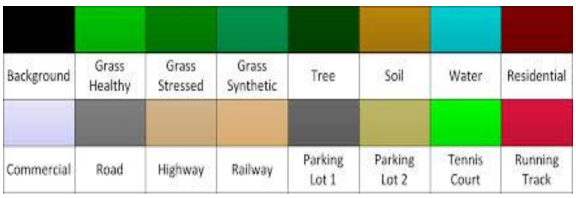
Gabor filters can encode shape and texture with different scales and orientations for HSIs. Fig. 1 shows a band of an HSI filtered by a Gabor filter. We can find that therectangular areas of the Gabor filter result contain more useful discriminative features than those of the original HSI. On the other hand, CNNs have achieved impressive results for HSI classification compared with traditional methods.

However, it requires a large number of labeled training samples, which are difficult to collect. Because Gabor filters can extract good convolutional features without training processing, and it is hard to obtain Gabor-like filters automatically when training CNN, we are inspired to incorporate Gabor filters and learnable convolutional filters for HSI classification.



Hyper spectral image (HSI) classification

Because the original HSI has hundreds of channels, we usually use some dimensionality reduction methods to compress the data before feeding it for the network. HSI reduction methods have two categories. The first one is feature exaction, which combines some bands to generate new features. The other is feature selection, which just drops some redundant bands.



Although there are many dimensionality reduction methods, we found that using principal component analysis (PCA) as the initialization method can obtain better performance for the proposed method. So, we first apply PCA to reduce the dimensions to 20 principal components.

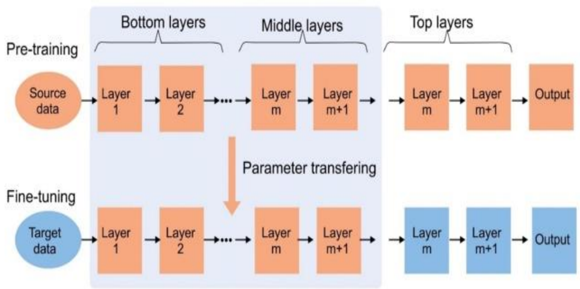
Algorithm:

Many HSI classification algorithms have been proposed over the past decade, including subspace-based methods, support vector machine (SVM), extreme learning machine (ELM), sparse representation classifier (SRC), lowrank representation, extended morphological attribute profiles (EMAPs), invariant attribute profiles (IAPs), etc.

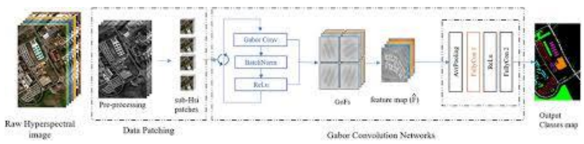
Deep-learning-based methods have drawn much attention recently in image classification. Deep learning uses a neural network with multiple hidden layers to automatically learn features from the original image, layer by layer. Due to its excellent performance, deep learning has been applied to HSI classification, with better results compared to conventional shallow methods.

Data Description and Experimental

The false-color image, ground truth, and corresponding class names of the Indian Pines data are shown. The experiments were conducted in two parts. The first part compared the proposed method and other state-of-the-art methods.



The second part analyzed the impact of different parameters of the proposed method. If not specified, we repeated the experiments five times to report the mean performance. The overall accuracy (OA), average accuracy (AA) (the average of the accuracies for each class), and Kappa coefficient were utilized to quantitatively estimate different methods.



According to the results, we can find that the fewer the training samples the more improvement the proposed method obtains. With fewer training samples, the accuracy of the proposed method only decreases slightly, while that

International Journal of Engineering, Management and Humanities (IJEMH)
Volume 4, Issue 5, Sep.-Oct., 2023 pp: 212-218 www.ijemh.com

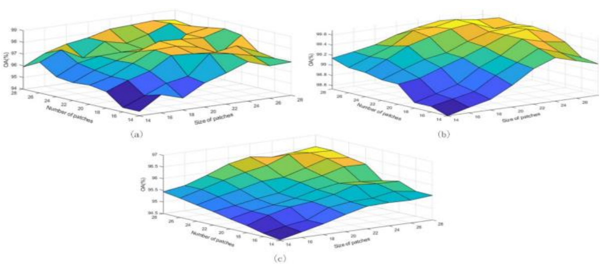
of the other methods dramatically declines, especially on the Salinas dataset

Conclusion:

In this article, we have proposed the GEF, which filters each input channel by fixed Gabor filters together with learnable filters, followed by some learnable 1 × 1 filters to generatethe output channels. Based on the proposed GEF, we designed a network architecture for HSI classification. To learn more discriminative features and an end-to-end system at the same time, we proposed to introduce the local discriminant structure for cross-entropy loss by combining the triplet hard loss.With limited training samples, the proposed method performs significantly better than other state-of-the-art HSI classification methods. Moreover, the proposed method is fast for both training and testing. However, the proposed method cannot obtain higher accuracy for normal image classification, because the input for the proposed network is a small image patch with many channels, which is only designed for HSI classification with limited training samples. For normal image classification, an image is a sample. When there are millions of training samples, the network should be much more complex and deeper to obtain better performance.

Comparison of Classification Maps:

The classification maps of different methods using training samples per class on the Salinas dataset and the Indian Pines dataset, respectively.



We can easily find that many regions of the classification maps achieved by the proposed method are obviously more accurate than those of CNN-DR, CNN-Gabor, and CNN-Capsule.

Future Work:

In our future work, we will investigate how to improve the proposed method for the normal image classification task, and how to combine other conventional features with CNN to obtain better performance.

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