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CNN Based Spectral Mixture Analysis

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Abstract: *In image analysis mixed pixel problem is common. The composition of the various object in a single pixel makes identification of genuine class more difficult. Subpixel algorithms give the better idea about the respective class of such pixels. The subpixel mapping method is varies depending on the type of image. In Panchromatic or multispectral images the data set is very less as compared to the hyperspectral image. A hyperspectral image contains contiguous bands. Each band is very narrow with few nanometer bandwidths. More than a hundred such band are available in the hyperspectral image. This huge data set is very difficult for the typical neural network to process. The feedforward neural network is not able to reach the local minima whereas the back propagation neural network needs a lot of time to converge to a minimum value. Radial basis function neural network has some advantages over other but it gives poor performance on hyperspectral imaging. The convolutional neural network is going to resolve the huge data problem. It has a 3-dimensional vector in which we can take multiple kernels to operated on interesting data. This kernel gives us depth which is nothing but the more information of the same pixel. So here we can save a lot of information as compared to other neural networks. But in the convolutional neural network after the pooling layer, our data is in a 3D form which we need to convert again in 1D by flattening.*
Keywords: *CNN, HSI,Spectral Unmixing, Subpixel mapping , Backpropagation.*

I. Introduction

Remote sensing techniques are the most popular methods nowadays to collect information without physical contact. Earth surface analysis is easier through remote sensing. Panchromatic images can collect most of the information of the interested area. The good spatial resolution images will give a better idea of the earth surface. But only spatial resolution will not enough to do analysis because of the presence of clouds and haze. Spectral information is also used to collect data from the surface. Radiometric resolution is also important in satellite imaging. More the bits per pixel more will be the grey levels. But there is difficult to get all this resolution at a time. Somewhere we need to compromise in resolution. There is another problem in satellite imaging called mixed pixel. In course resolution mixed pixel problem is common. While doing an analysis of such images then the accuracy of the images decreases because of the mixed pixel. The subpixel sharpening and subpixel mapping are the techniques introduced by Atkinson in 1997. Subpixel mapping improves the accuracy of the image by soft classification. Mixed pixel is nothing but a single pixel contains many objects. In such situation classification of that pixel in a single pixel is very difficult. In the satellite image, there are many objects. The pixel having information more than one class where we need to handle data very carefully otherwise this situation leads towards misclassification of data. The algorithm is given by Atkinson which resolves most of such cases by dividing a pixel into subpixel. Then those subpixels are mapped to respective classes. A lot of research is going in such directions but the algorithms do not perform well in all directions.[5] Some algorithm gives good classification accuracy but fails in the convergence criterion. In this paper, we provide an overview of existing techniques for unmixing. Objectives of paper are given in section 2. Section 3 describes the various methods available for subpixel unmixing and comparison among them. Section 4 describes the Convolution Neural Network method for unmixing hyperspectral data. Section 5 concludes with the future scope.

II. Objectives

In Remote sensing, the data is received at the sensor not only from the targeted area but also from the path radiance. The path radiance is nothing but an error in the reflected value due to scattering phenomena. The first objective of this survey paper is to study methods to remove the path radiance from the image. The second objective of this survey paper is to understand techniques to remove haze and clouds from the image. The third objective is to learn how to improve the accuracy of classification by using subpixel mapping.

III. Methodology

The panchromatic images give good spatial resolution but this data does not give enough idea about the mixed pixel. The multispectral images will give certain spectral information. The multispectral resolution adds the more information in overall classification result. Still, these bands are less in numbers due to that, all the spectral responses will not be recorded. Hyperspectral images are providing maximum information of images because there are more than 100 spectral narrow bands available. In subpixel mapping, those bands will give detail information about the mixed pixel. Such a huge information is more suitable for mixed pixel classification. CNN is used to handle such kind of data as CNN has multiple kernels. This multiple kernel gives depth to the neural network. With this multiple kernels, the multiple bands present in the a hyperspectral image can be easily studied.

3.1 Path Radiance

Scattering is an important factor to reduce the reflectance. Rayleigh scattering is occurred due to the gas molecules present in the images. Rayleigh scattering will be assumed to be homogeneous in all the images. Due to Rayleigh scattering, the reflectance values are increasing homogeneously. So by identifying the histogram of each band we will get an idea about the path radiance or offset. By subtracting that offset value from each pixel Path radiance can be removed. Path radiance subtraction also called as dark object subtraction[7].

$$R= \frac{(L_s - L_p)\times \pi d^2}{E\cos\Theta T} \qquad (1)$$

In the above equation, L_s is Total radiance received at the sensor, L_p is path radiance, E is solar spectral irradiation, d astronomical distance between earth and sun, θ is solar elevation angle [7].

3.2 Removal of haze and clouds

Haze optimization transform is giving better result in the cloudy and hazy image. Scatter plot of blue wavelength Vs Red wavelength will give an idea about Haze vector. Haze vector tells us about haze and cloud content in the particular image. After subtracting Haze vector from respective pixel we get the haze free image.[7]

3.3 Sub Pixel Mapping

In subpixel mapping there is a lot of work has been done. The various algorithm includes back propagation neural network method, some are based on a modified version of backpropagation i.e. observation model. Also, some methods are based on the neural network with a predicted coefficient and few are based on radial basis function neural network. The subpixel sharpening and subpixel mapping methods with wavelet multiresolution analysis enhance the resolution of soft classification by using multiresolution decomposition. The image is decomposed at a different scale and process the approximations, vertical, horizontal and diagonal information. Each data is separately given to the NN and the highest probability is calculated from two classes [2].

The basic problem of the regression model is eliminated by updating the weighted of the neuron links. Here nonlinear sigmoid function is used as an activation function which improves the quality of learning. In this paper, certain problems related to Backpropagation have been addressed like local and slow convergence speed. Here weight is adjusted by adjusting the learning rate and momentum coefficient. The local subpixel mapping model can be obtained by finding the relationship between fractions in the local window and the spatial distribution.[3] Liangpei discussed two methods in his paper. In the first method, the subpixel assigns to class with the maximum output value. This method works better if the data set is small with few classes. The second method keeps the records of the fractions of the different classes. Those fractions values are then weighted in respect to a sum of the output in the selected subpixel set. The modified BPNN method improves the accuracy as compared to BPNN. Modified BPNN algorithm is giving a good result for only synthetic images [3].

Xiaodong Li and Yun Du works on fraction images generated through soft classification. They estimate in each pixel the area proportion of each class. Those images are taken as input for sub pixel mapping model to resolve the mixed pixel problem [4].

Qunming Wang, Wenzhong Shi and Peter M. Atkinson in the there paper discussed radial basis function. With the help of the basis function, the relation between the subpixel within the coarse resolution and the surrounding course resolution are quantized. Then the coefficient indication the contributions from neighboring course pixel are calculated. To predict the subpixel soft classification the basis function values are weighted by the coefficient. In the given paper, two major problems from subpixel mapping are addressed. The first problem is an identification of a total number of subpixels and second is about class label prediction of those subpixels. Super-resolution methods are more effective in RBF interpolation which gives point prediction. Soft class values are estimated by using RBF interpolation and Hard class values are estimated by class allocation. [5]

3.4 Convolutional Neural Network

CNN introduces in 1998 by Yann LeCun. There is various kind of spatial neural networks for processing data that is known as a grid topology. this can be a one dimensional time series data or grid of samples over time series data or something like 2 dimensional image data a grid of pixel in space.[6]

CNN has 3 features that reduce the number of parameters in NN.

3.4.1 A sparse interaction between layers

In typical NN every neuron in one layer is connected with every neuron in the next layer. This means a large number of parameter networks needs to learn which cause many problems in learning. i.e. to learn a lot of parameters we need more training data and convergence time also increases and we may end with an overfitted model. CNN can reduce the number of the parameter throughout the indirect interaction.

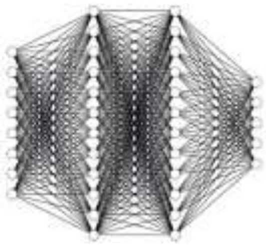

Figure 1: Typical Neural Network

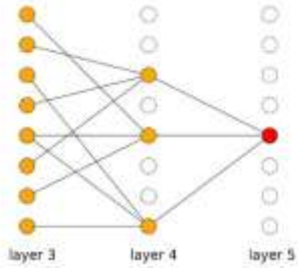

Figure 2: Convolution Neural Network

3.4.2 Parameter sharing

This further reduces the learning parameter as sparse interaction. it is important that CNN have spatial features interaction.

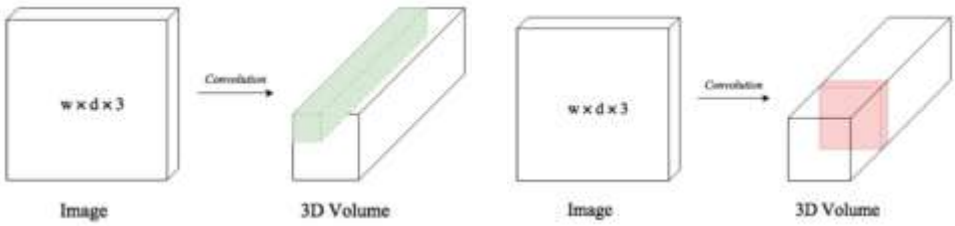

Figure 3: Parameter Sharing

An image after passing through convolution layer gives rise to a volume. then a section of a volume taken through a depth representation features of a same part of the image. Furthermore, each feature in the same depth layer is generated by the same filter that convolves the image. Feature map is created for the same set of shared parameter. This drastically reduces the number of the parameter to learn to run typical ANN.

3.4.3 Equivariant Representation

A function f is said to be equivariant to another function g if. $f(g(x))=g(f(x))$ for e.g. convolution is equivalent to translation operation that means if an image is convolving first and then translating is equivariant to translating first then then convolving.

Figure 4: Convolution and Translation

The convolution layer gives the edges however smiler edges may occur in the entire image. So make sense to represent them with the same parameter. Types of layers in CNN

3.5 Types of layers in CNN

3.5.1. Convolution Layer Convolution Layer

It is the first layer in CNN in which we convolve the data or image using kernel or filter. Convolution operation involves taking elementwise a product of the filter in the image and then summing those values for every sliding action. Percentage of the area of g filter that overlaps the input at a time Ʈ overall time t. This is a single dimension convolution operation. For the multidimensional input we required multidimensional kernel.

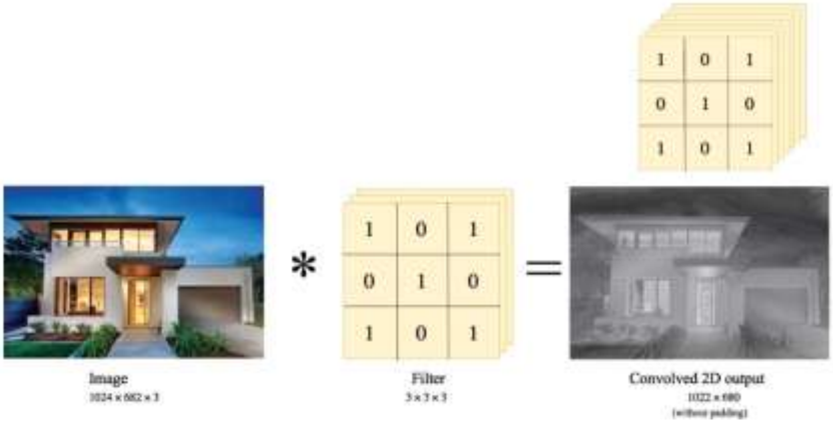

Figure 5: Multiple Kernal

3.5.2 Activation Layer

In CNN nonlinear activation the function is preferred because of there is no any learning if we used a linear activation function. Typically reLu the activation function is used in CNN but to avoid Dying Relu problem preferably Leaky Relu is activation fiction is used.

3.5.3 Pooling Layer

Pooling involves a down sampling of the features. So that we need to learn less parameter during training. There are two hyper parameters are mention in pooling layer.

(a) Dimension of Spatial extent
(b) Stride

Depth of the image remains unchanged after pooling layer. Pooling reduces the chances of over fitting as there are less parameters.

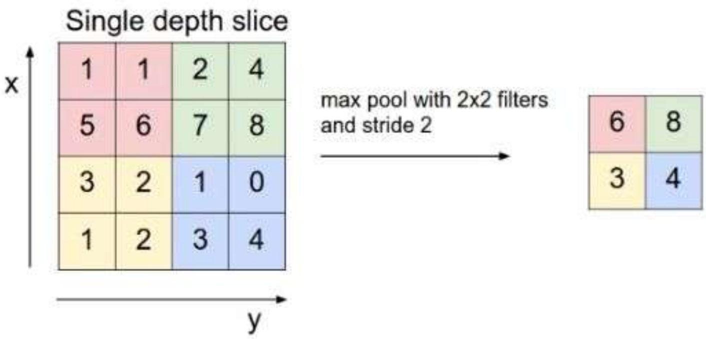

Figure 6: Down sampling with Stride of 2 [11]

In pooling we reduces the 25 % of number of features this is significant decaying in number of parameters.

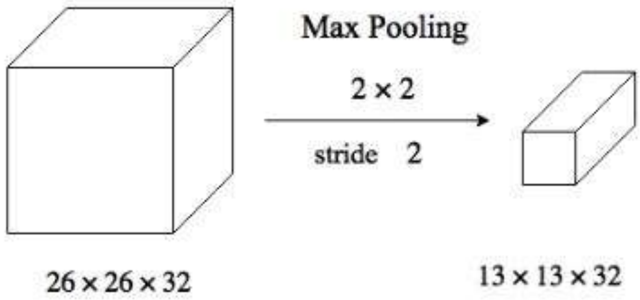

Figure 7: Max Pooling

3.5.4 Fully Connected Layer

The fully connected layer is the simplest method to learn nonlinear combination features. Convolution layer provides meaningful, low dimensional and invariant feature space and the fully connected layer is learning a possibly nonlinear function in that space. The output of the pooling layer is 3D feature map and fully connected layer remains a 1D feature vector.

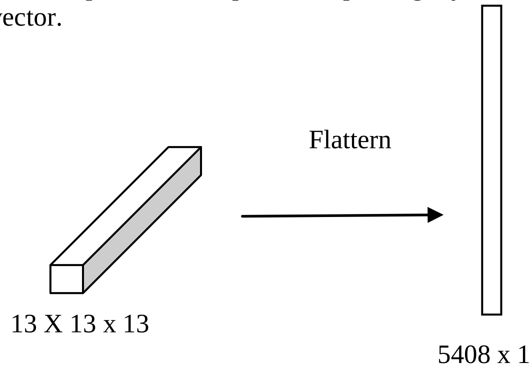

Figure 8: Flattening

Convolution, Activation, and pooling layer may occur many times before Fully connected layer and hence the depth of the filter is an increase. So, by flattering a 3D layer is converted into 1D vector. Here the output of fully connected layer is applying at the softmax activation to the last layer of neurons.

IV. Summary

In subpixel unmixing, the most important is an availability of data. If we have only spatial information then its very difficult to separate the mixed pixel. The subpixel is not well distinguished from the neighborhood which results in reduced in the accuracy. The subpixel to be classified correctly the probability must be more than half within two adjacent classes. We observe that the classification accuracy of feed forward neural network, Back Propagation neural network and radial basis function neural network is less. These neural networks cannot be able to handle a large dataset.

4.1 Future Scope

Furthermore, network performance can be increased by adding information to the training dataset. This additional information makes uses of physical characteristics of objects. Specific spectral bands are combined to form a discriminative index. For example, the normalized difference vegetation index discriminates vegetation from non-vegetation. Further research could also address the effects of increasing the number of training samples subject to a wider range of weather conditions. This possibly enhances segmentation performance when training a network using a training dataset subject to multiple weather conditions.

4.2 Summary

Convolutional neural networks are capable of generalizing HS images under varying lighting, weather and seasonal conditions. In this application, neural network design is a segmentation accuracy is controlled by network weight arrangement. A wavelet-based method is giving the simple solution for unmixing the subpixel but at a certain scale. Backpropagation which is a special case of feedforward neural network which will address the problems related to weight adjustment but still, time requires to converge the network is large. Radial basis function gives better classification as a basis function is Gaussian-based which is influencing more near to the center and influence decreases as we move away from the center.

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