

Land Use Image Classification Using Deep Learning Networks

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Abstract-- Classification is considered as one of the important topics in remote sensing. For classification of land use image, the detection of many objects present in the land is highly essential. Large number of methods was proposed for data classification problem. Most of these method do not extract deep features. In this paper, deep learning concept is introduced to extract deep features. In this paper, the concept of Convolution Neural Networks (CNN) is introduced into data classification. The proposed work consists of three phase. In first phase, ZCA Whitening is applied to the land use image. The mean value and optimized theta is calculated for ZCA Whitening and combined into dataset. In second phase, the features are extracted using Convolution and Pooling. In third phase, the features are used for classification.

Index Terms – Convolutional Neural Network (CNN), ZCA Whitening, Convolution, Pooling.

I. INTRODUCTION

Spectral image data is a branch of spectroscopy and of photography in which a complete spectrum or some spectral information. These image data are considered as a important tool for monitoring Earth's surface. But there are several problems in the classification of spectral data: 1) limited number of labelled training samples 2) large spatial variability of spectral signature.

Several classification methods have been proposed to deal with data classification of remotely sensed images. There are some traditional approaches for data classification such as k-nearest neighbours, minimum distance, parallelepiped classification, multi-scale segmentation etc. The above methods suffer a lot if high numbers of spectral channels are used. To deal with the problem of curse of dimensionality, some method should be proposed which reduces the dimensionality for classification.

In this paper, we introduce convolutional neural network which is one of deep learning based feature extraction for data classification. Our work focuses on applying zero-phase component analysis(ZCA) Whitening, extracting the features using convolution and then applying the pooled features for classification.

Our method is to extract the sub image based on the vector of intensity values per pixel using deep learning concept and then extracting the feature maps for classification.

II. RELATED WORK

In the last two decades many approaches regarding the classification of remotely sensed image were introduced. The Support Vector Machine (SVM) is considered as one

of the classifiers which can obtain better accuracy. Recently, neural network concept proved that they can obtain better accuracy when compared to Support Vector Machine

Marco Castelluccio [2] modified two architecture CaffeNet and GoogLeNet, with three different learning modalities. This modified architecture made them to avoid overfitting problems and reduce design time.

Yushi Chen [4] [5] proposes two concept in the area of deep learning. They are stack encoder and Deep belief networks. The framework of stack encoder includes Principle Component Analysis(PCA), Deep learning architecture and logistic regression. The stacked autoencoders aim to uses high level features.

Qin Zou [3] proposes deep belief network which achieves feature abstraction by minimizing the reconstruction error over the whole feature set.

Adriana Romero[1] proposes a highly efficient algorithm for unsupervised learning of sparse features. Standard principal component analysis (PCA) and its kernel counterpart (kPCA) were used as a framework for learning representations of data.

III. METHODOLOGY

The detailed work of the system is given in Fig 1. The main objective of the proposed work is to classify the remotely sensed image into a thematic map i.e, to label the group of objects. The object is labelled by constructing a deep learning network using appropriate spectral features.

The input image is given as land use spectral image, then ZCA Whitening is applied to reduce the dimensionality of the data. The mean value and optimized theta is calculated

for ZCA Whitening and combined into dataset. Then the features are extracted using Convolution and Pooling. Finally, the pooled features are used for classification.

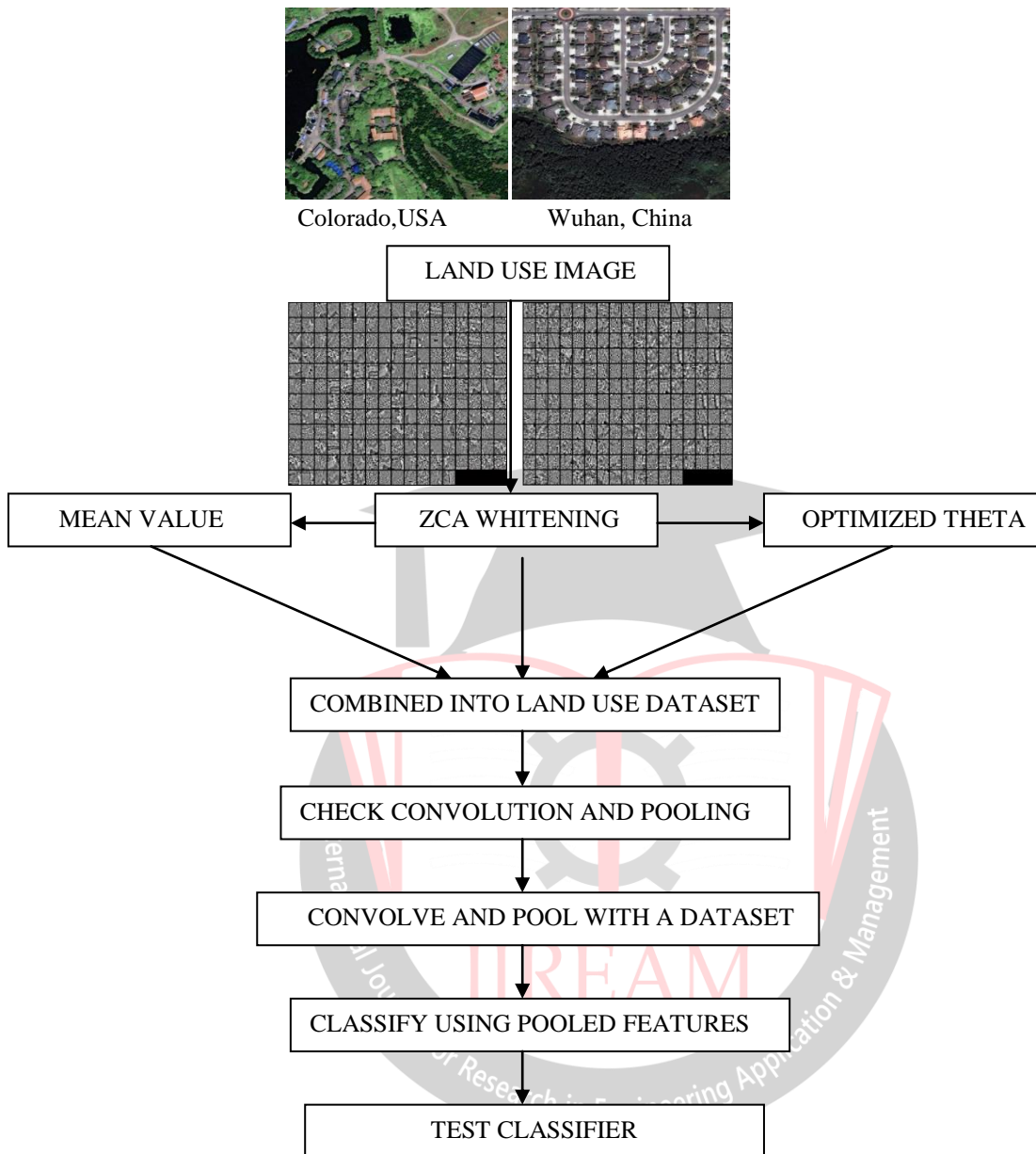


Figure 1. Proposed Classification Approach

IV. DEEP LEARNING, CNN

A. DEEP LEARNING

In early papers, three layer nets are proved via Fourier ideas. This shows any continuous function from input and output can be implemented using three layer net. But these method could not train a layer properly.

Deep learning involves a class of model used to learn deep features of input data, which are deeper than three layers. In deep learning, an image can be represented in many ways such as a vector of intensity values per pixel, set of edges, regions of particular shape, etc.

The deep learning network architectures include deep belief networks (DBNs), deep Boltzmann machines (DBMs), Stacked Auto Encoders (SAEs), and stacked denoising AEs (SDAEs). One of the layer-wise training model of deep learning network is Convolutional Neural Network which is used in our proposed work.

B. CONVOLUTIONAL NEURAL NETWORK

Due to the impressive result in image classification, the interest for Convolutional Neural Network has been growing fast. The convolution neural network is evolved from Multilayer Perceptron. The main disadvantage in MLP is setting large number of free parameters. These may result in huge training set and exceeding large

computational power. These problems can be solved by Convolutional Neural Network.

The architecture of a CNN is designed to take benefit of the two dimensional structure of an input image.

1) Convolutional layers: The convolution of the input image is computed by the weights of the network. Neurons in the first hidden layer view a small image window, and learn low-level features. However, the deeper layers view larger portions of the image, and are able to learn more features by combining low-level ones.

2) Pooling layers: reduce the size of the input layer through some local non-linear operations, for example max or mean pooling use reduce the number of parameters to learn and provide some translation invariance.

3) Fully-connected layers: are typically used as the last few layers of the network. Figure 2 represents the

Convolutional Neural Network based on locality. Here L1, L2, L3, L4 represents the convolution and F5, F6 represents the Fully connected network

V. USING CNN FOR LAND USE IMAGE CLASSIFICATION

In this paper, we use CNN for land use image classification. For convolution we take some training datasets in RSSCN7.

In first stage, we have used ZCA to reduce the dimension of the data. If we are training an image, the raw input will be redundant, since the adjacent pixel values are highly correlated. The goal of whitening is to make the input less redundant.

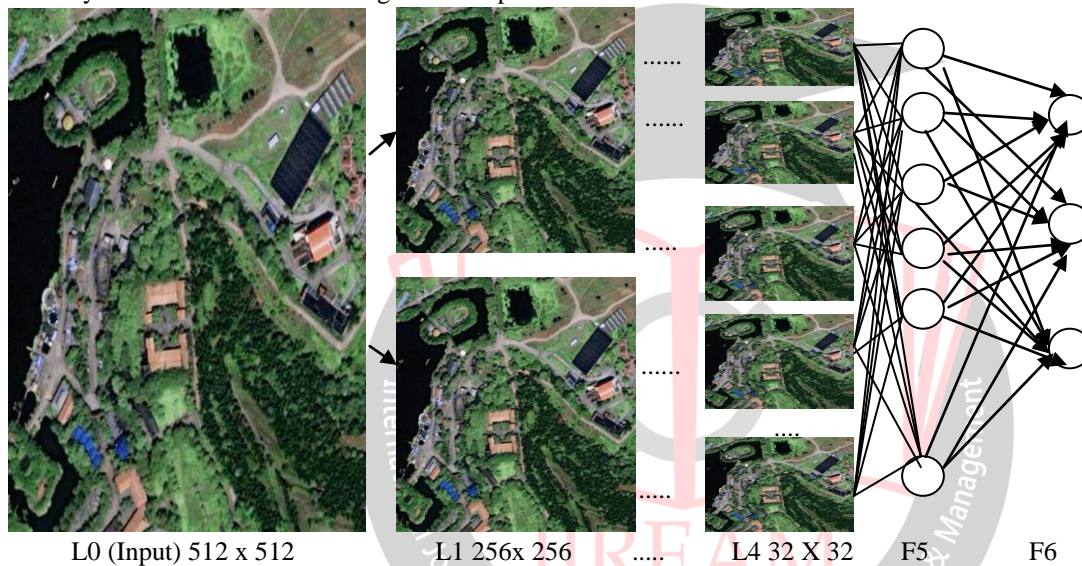


Figure 2 CNN Learned Features

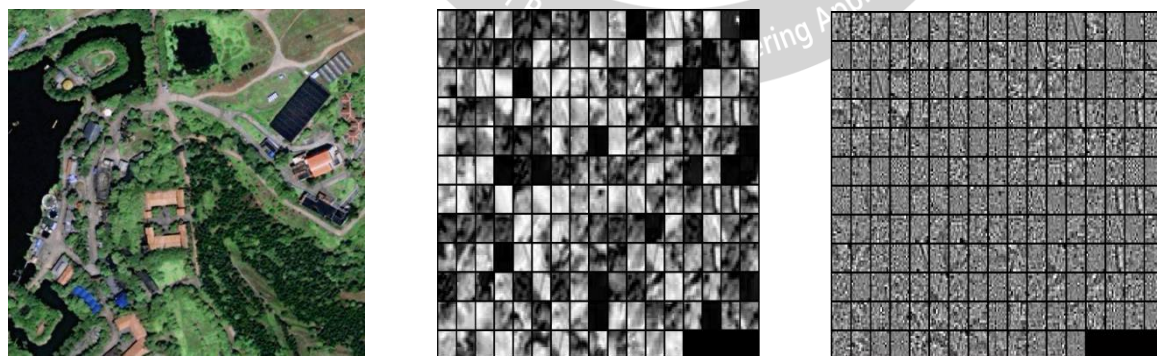


Figure 3 a) Original Image

3b) Raw Image

3c) ZCA Whitening

Figure 3 a) represents The Wuhan image data was acquired in a rural area of Wuhan, China. Figure 3 b) represents the raw data obtained by random selection of 200 samples. Figure 3 c) represents the ZCA Whitening obtained from the raw data.

ALGORITHM 1: ZCA WHITENING

1. Begin
2. Initialize x as the original image
3. Randomly select a patch of an image i.
4. For every patch of the image
 - a. Compute the mean pixel intensity value separately.

5. End
6. Calculate the value of sigma by taking x as data structure that contains one training example per column.

$$\Sigma = \frac{1}{m} \sum_{i=1}^m (x^{(i)})(x^{(i)})^T$$

(1)

7. ZCA computes the eigenvectors of Σ .
8. The rotation is performed by the product of eigenvectors to the translation of data structure x.
9. Finally, ZCA is calculated by the following formula,

$$\frac{x_{rot,i}}{\sqrt{\lambda_i + \epsilon}} \quad x_{ZCAwhite,i} = U * \quad (2)$$

In the next stage, the feature extraction takes place using convolution and pooling.

ALGORITHM 2 : CONVOLUTION

1. Begin
2. for each image row in input sub image:
3. for each pixel in image row:
4. for each kernel row in kernel:
5. for each element in kernel row:
6. if element position corresponding to the pixel position then
7. multiply the element value corresponding to pixel value
8. add result
9. endif
10. set output image pixel to pooling
11. end

There are certain conditions for obtaining feature maps by performing convolution between sub image and kernel. They are as follows

- The input to a convolutional layer is a $m \times m \times r$ image where m is the height and width of the image and r is the number of channels
- The convolutional layer will have k filters (or kernels) of size $n \times n \times q$ where the value of n is less than the dimension of the image and q can either be the same as the number of channels r or less for each kernel.
- The size of the filters gives rise to the locally connected structure which are each convolved to produce k feature maps with the size $m-n+1$.

After obtaining features using convolution, we would next like to use them for classification. But the features extracted in convolution cannot be directly applied to classification due to high number of parameters.

Thus, to describe a large image, one natural approach is to aggregate statistics of these features at various locations of the images. For example, we can compute the mean (or max) value of a particular feature over a region of the

image. These features are much lower in dimension and can also improve results. This statistics can be done by pooling.

VI. EXPERIMENTAL RESULT

We have used two images for our work: Colorado and Wuhan. The Colorado image data was captured in a residential area in Colorado, United States. The size of the image is 512×512 . Wuhan image data was acquired in a rural area of Wuhan, China. The size of the image is 2437×1793 . The spatial resolution of this image is about 2.44 m per pixel.

We have also used some training images from RSSCN7. This data set contains 2800 remote sensing images, which consists of seven typical scene categories. The scene categories are grassland, forest, farmland, parking lot, residential region, industrial region, river and lake. Each category contain 400 images. Each image size is 400×400 pixels. These dataset are captured under changing seasons and varying weathers. Some sample images are shown in Fig. 4

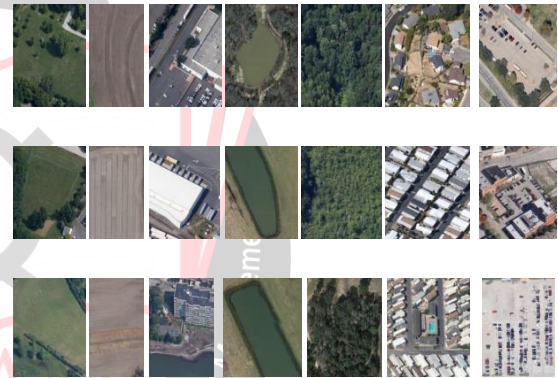


Figure 4 Sample images from RSSCN7 dataset. From left to right (columns) : grassland, farmland, industrial regions, lake, forest, residential region and parking lot.

The measurement such as overall accuracy, average accuracy and kappa coefficient should be calculated after classification to prove that our method is better than the existing method.

VII. CONCLUSION

Thus the ZCA Whitening process is performed to make the image into less redundant and the algorithm for convolution for sub image is constructed. Further, the features should be extracted from convolution and pooling and then features extracted from pooling are used for further classification.

REFERENCES

- [1] Adriana Romero, "Unsupervised Deep Feature Extraction for Remote Sensing Image Classification," IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING.

- [2] Marco Castelluccio, "Land Use Classification in Remote Sensing Images by Convolutional Neural Networks" arXiv:1508.00092v1 [cs.CV] 1 Aug 2015
- [3] Qin Zou, "Deep Learning Based Feature Selection for Remote Sensing Scene Classification" IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 12, NO. 11, pp 2321-2326, NOVEMBER 2015.
- [4] Yushi Chen, "Deep Learning-Based Classification of Hyperspectral Data" IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 7, NO. 6, pp 2094-2107 JUNE 2014.
- [5] Yushi Chen, "Spectral-Spatial Classification of Hyperspectral Data Based on Deep Belief Network" IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 8, NO. 6, pp. 2381- 2392, JUNE 2015

