Land Use Classification using Deep Convolutional Neural Network

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Abstract

One of the challenging issues in high-resolution remote sensing images is classifying land-use scenes with high quality and accuracy Land use classification is required to measure land and its impact on ecosystem. Deep learning is a powerful state-of-the-art technique for image processing including remote sensing images. Land use is classified for environmental monitoring, urban planning and resource management. This proposed system will use in the UC Merced land-use data set. The preprocessing the image can make the improving of image positional accuracy, reducing the storage space, the improving the spectral qualities of image. The pretrained CNN is initially used to learn deep and robust features. Then, the feature extractor of CNN mapps the features and the fully connected layers of CNN are used to obtain excellent results.

Keywords- Classification, Deep Learning, Land Use

1. Introduction

Land-use classification with remote sensing image is always a hot issue in remote sensing technology, which refers to a process that classifies each pixel in remote sensing image into realistic land-use objection. Along with the rapid increase of remote sensing image data and the gradual improvement of resolution, land-use classification with remote sensing image technology plays a more and more important role in urban planning, environmental protection, resource management, mapping and other fields. Deep learning has attracted the interest of many researchers, and becomes a wave of big data and artificial intelligence. Deep neural network simulates the multilayer structures of human brain, abstracts the original data to get features which are applicable for classification. Nowadays, deep learning has achieved great success in recognition of handwritten character, speech and other fields, and offered new thought for land-use classification with remote sensing image. In this paper a approach for land-use classification with remote sensing image based on CNN is proposed, which is verified by the remote sensing data UC-Merced data set.

2. Related Works

In literature, [1] land use classification method based on stack autoencoder has been proposed by Anzi Ding, Xinmin Zhou. This method is tested in GF-1 images with 4 spectral bands and spatial resolution of 8 m. They show that the method based on SAE is more accurate in classification result than support vector machine and back propagation neural network. In [2], Anqi Wang, Peng Liu and Chao Xie have proposed Markov random field texture classification method. This method is used in German TerraSAR-X radar data. [3]Dino Ienco, Raffaele Gaetano, Claire Dupaquier, and Pierre Maurel have proposed land cover classification method based on Deep recurrent neural networks. This proposed model has validated on two different data set showing that this framework efficiently deals with both pixel- and object-based classifications. [4]Deep convolutional neural network for land-cover classification method has proposed by Grant J. Scott, R. England, William A. Starms, Richard A. Marcum and Curt H. Davis.

3. Theory Background

The CNN is a trainable multilayer architecture composed of multiple feature-extraction stages. Each stage consists of three layers: 1) a convolutional layer, 2) a nonlinearity layer, and 3) a pooling layer. The architecture of a CNN is designed to take advantage of the two-dimensional structure of the input image. A typical CNN is composed of one, two, or three such feature-extraction stages, followed by one or more traditional, fully connected layers and a final classifier layer. Each layer type is described in the following sections.

3.1 Convolutional Layer

The input to the convolutional layer is a three-dimensional array with r two-dimensional feature maps of size m × n. Each component is denoted as $x_{m,n}$, iand each feature map is denoted as x^i. The output is also a three-dimensional array $m_1 \times n_1 \times k$, composed of k feature maps of size $m_1 \times n_1$. The convolutional layer has k trainable filters of size l × l × q, also called the filter bank W, which connects the input feature map to the output feature map. The convolutional layer computes output feature $z^s = \sum_{t=1}^{q} \quad W_i^s x^i b_{si}$ where * is a two-dimensional discrete convolution operator and b is a trainable bias parameter.

3.2 Non Linearity Layer

In the traditional CNN, this layer simply consists of a pointwise nonlinearity function applied to each component in a feature map. The nonlinearity layer computes the output feature map $a^s = f(z^s)$, as f(.) is commonly chosen to be a rectified linear unit (ReLU) $f(x) = \max(0,x)$.

3.3 Pooling Layer

The pooling layer involves executing a max operation over the activations within a small spatial region G of each feature map: $P_G^s = \max_{i \in G} a_1^s$ .To be more precise, the pooling layer can be thought of as consisting of a grid of pooling units spaced s pixels apart, each summarizing a small spatial region of size p * p centered at the location of the pooling unit. After the multiple feature-extraction stages, the entire network is trained with back propagation of a supervised loss function such as the classic least-squares output, and the target output y is represented as a 1–of–K vector, where K is the number of output and L is the number of layers

$$J(\theta)=\sum_{i=1}^{n}(\frac{1}{2}\parallel h(x_i,\theta)-y\parallel^2 + \boldsymbol{\lambda}\sum_{\mathbf{1}}^{\boldsymbol{L}}\boldsymbol{sum}(\parallel \boldsymbol{\theta}^{(\mathbf{1})}\parallel^{\mathbf{2}})$$

where l indexes the layer number. CNNs have recently become a popular DL method and have achieved great success in large-scale visual recognition, which has become possible due to the large public image repositories , such as ImageNet.

4. Proposed System

4.1 Image Preprocessing

Preprocessing tasks include geometrically correcting imagery to improve the positional accuracy, compressing imagery to save disk space, converting lidar point cloud data to raster models for speed up rendering in GIS systems and correcting for atmospheric effects to improve the spectral qualities of an image.

4.2 Pretrained CNN

The deep convolutional features learned by pretrained CNN are sufficiently discriminative for land use classification. For classification, CNN will be trained on UC Merced land-use data set by Matlab. CNN network can learn features and get a better performance even with limited data set.

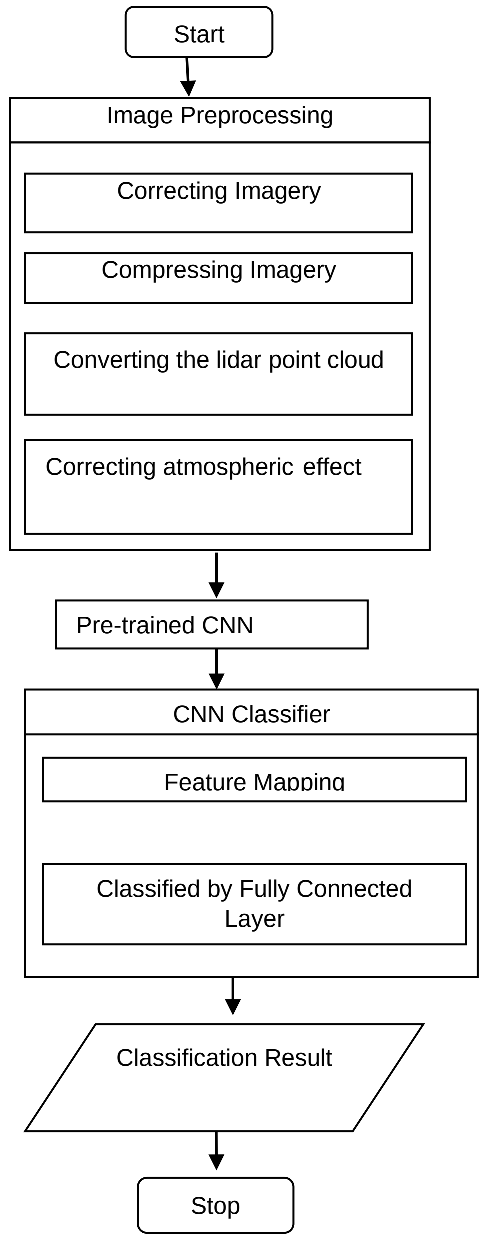

Figure 1. Proposed System

4.3 CNN Classifier

The input image passes to the first convolutional layer. Then, after multiple layers of convolution and padding, the output in the form of a class is needed. The convolution and pooling layers would only be able to extract features and reduce the number of parameters from the original images. The Feature extractor of CNN maps the features. A fully connected layer is needed to generate the final output equal to the number of classes.

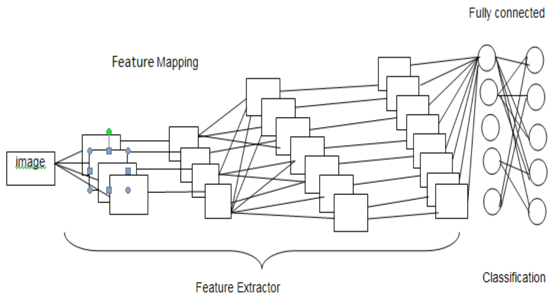

Figure.2 CNN Classifier

4.4 Dataset

The UC Merced land-use data set is investigated, which is a set of aerial orthoimagery with a 0.3048-m pixel resolution extracted from United States Geological Survey national maps. The UCMerced data set has been used as a benchmark for land use classifier evaluation in numerous publications .The data set consists of 21 land-use classes containing a variety of spatial patterns, some with texture and/or color homogeneity and others with heterogeneous presentation. The data set was compiled from a manual selection of 100 images per class, each RGB image being approximately 256 × 256 pixels. The 21 land-use types include agricultural, airplane, baseball diamond, beach, buildings, chaparral, dense residential, forest, freeway, golf course, harbor, intersection, medium density residential, mobile home park, overpass, parking lot, river, runway, sparse residential, storage tanks, and tennis court classes.

5. Conclusion

The Land use and land management practices have a major impact on natural resources including water, soil, nutrients, plants and animals. Land use information can be used to develop solutions for natural resource management issues such as salinity and water quality. In future work, we will try to use the benefit of using convolutional neural network (CCN) to perform land use classification via remote sensing images.

6. References

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