Transferring Deep Belief Networks for the Classification of LANDSAT8 Remote Sensing Imagery

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Abstract. This paper studies the structure and characteristics of LANDSAT8 OLI data, and transfers Deep Belief Networks model to OLI datasets. Firstly, the sub-sampling window is used to filter the pretraining data, which reduces the calculation cost of the hidden layer feature representation of the model. The parameters of each layer of DBN are trained forward, optimization parameters are used to make the error converge to a low value in back propagation. Finally, the activation function is used to reduce the dimension of the hidden layer of the model, and the output vector is used as the global feature representation of the image. Running DBN to complete the classification of LANDSAT8 remote sensing image in the study area, the experimental results show that the model has completed the classification and achieved high user accuracy and reliability in the case of that all types of the wetlands have similar spectral characteristics. The conclusion is that the pretrained features can be well applied to the LANDSAT8 remote sensing datasets. The accuracy is improved within the scope of cost calculation, and the local minima problem will also occur in deepening model.

1. Introduction
In the past 20 years, high-resolution remote sensing(HRRS) image classification has been an important means of extracting image information. For many practical remote operations, it is a basic task to classify image data into different semantic categories, and it also plays a key role in the application fields of various industries. In recent years, deep learning technology has achieved great success in the field of image recognition. As a new research direction, it has received great attention in the field of HRRS image processing [1-4]. Deep belief network (DBN) algorithm is a kind of neural network for machine learning. Unlike the earlier multi-layer perception model, which can only do simple linear classification, DBN has a wide range of applications and strong expansibility. In addition to using DBN to identify features and classify data, it can also be used to predict data [5-9]. In the past 40 years, LANDSAT satellites have played an important role in enlightening and promoting the development of remote sensing application technology, and their remote sensing image data have been widely used in China[10-12]. Aiming at the difficulty of classification and information extraction of features with similar spectral features in LANDSAT8 datasets, a classification method based on DBN model was studied. It was thoroughly investigated that how to effectively use DBN activations from not only the training of RBM hidden layers but also the back propagation as the iteration error control, and then transfer DBN model for the classification of LANDSAT8 remote sensing imagery to resolve the difficult of information extraction within wetlands.
2. DBN Model

DBN is a probability generating model. Compared with the traditional neural network, the generating model is to establish a joint distribution between observation data and labels. By training the weights among the units, the whole neural network can generate training data according to the maximum probability. Structurally, DBN consists of a multi-layer unsupervised restricted Boltzmann machine (RBM) network and a supervised back propagation network [13-14]. As shown in Figure 1, the connection between the outermost two layers of the model is undirected, forming the associative memory. The leftmost represents data vectors, each unit represents one dimension of data vector, and the right side is the output of feature vector and weight. The layers are connected with each other in a direction, which is composed of hidden units and used as feature detectors.

![Figure 1. Illustration of a typical Schematic of a DBN.](image)

RBM contains two layers of neurons, one of which is the visible layer, which are used to input training data, the other is called the hidden layer [15-16]. Each layer can be represented by a vector, using the data vector sampled by the previous layer to infer the hidden layer, and then treat this hidden layer as the data vector of the next layer. The pre-training process of RBM is to obtain the weight \( w \) by unsupervised greedy method layer-by-layer, and the best weight value makes the probability of the training sample maximum. In each layer from left to right, the parameters of the current layer RBM are fully trained. After the parameters are determined, the state of the hidden layer neurons of the current RBM is used as the input of the second layer. A stacked DBN consists of the above repeating steps.

The error of hidden layer can not be directly applied gradient descent, the output layer error is passed to the hidden layer with the help of the transposed weight matrix. Like the standard feed forward neural network, the weight matrix linked to the hidden layer is indirectly updated using the back propagation algorithm. The loss function derived from the training sample through the logistic regression is used to derive the loss function, where the error becomes signal input, using the chain rule to implement the update task for each layer parameters.

3. Classification based on DBN

3.1. Data features of OLI sets

As the eighth satellite in the series of LANDSAT satellites, LANDSAT 8 continues and advances the collection of LANDSAT data with a two-sensor payload. Two main sensors are the operational land imager (OLI) and the thermal infrared sensor (TIRS). OLI collects images using nine spectral bands in different wavelengths of visible, near-infrared, and shortwave light to observe a 115 mile wide swath of the earth in 15-30 meter resolution covering wide areas of the Earth's landscape while providing sufficient resolution to distinguish features like urban centers, farms, forests and other land uses[17-18]. Details of layer and wavelength of OLI Spectral Bands are showed in Figure 3.

OLI has a four-mirror telescope and data generated are quantized to 12-bit and improved to 16-bit, compared to the 8-bit data produced by the enhanced thematic mapper Plus(ETM+) sensor, the gray scale of the image is raised to 65535, which has high information content. Based interchange format for georeferenced raster imagery, datasets are stored in compressed Geo-TIFF format with
integer-16 each unit. Each data file is associated with an header file containing georeference information is to be converted into matrix or grid data frame.

3.2. Classification method

The same sample data exists in the same coordinate position of 9 bands image data after coordinate calibration. The objects of a certain class may have significant characteristics in the current band, or may have a small characteristic distance with other types. Therefore, nine datasets are trained with sampling samples. Usually, image samples is irregular, so the sampling areas are subsampled according to \((M+\Delta m) \times (n+\Delta n)\) adaptive size window. In the range of \(\text{max (row, column)}\), the sample pixel \(I_i\) is traversed, and the accumulated \(I/(m \times n)\) in the filtering window is recorded as \(U_k\), which is the representation of the pixels in the window.

![Figure 2. Subsampled data through filter window m×n.](image)

Two aspects, increased variance value and deviation of the estimated mean value caused by the limited size of the sampling window, are the main sources of sampling errors. In LANDSAT8 classification samples, the more information that is retained in LANDSAT8 samples, the lower standardized Euclidean distance, and the error effect is also reduced. The training samples are sampled under one layer, and the two-dimensional sample area is converted into one-dimensional pixel column to input DBN, which is a little more important in reducing the contribution of parameter dimension, and at the same time, it is more advantageous to transfer information to the next module for feature extraction.

![Figure 3. Classifier construction using OLI datasets.](image)

The overlapped RBM networks form a DBN structure to extract the characteristics of the objects to be processed. The probability of the output of the OLI datasets is the same as that of the samples, and
the maximum probability of the nine probability results is selected to determine the type. The classifier is designed as shown in Figure 3, and the implementation process is as follows.

(i) Select $k$ training samples of the target type (such as waters, shown in blue colour in false colour image) and convert them into one-dimensional sampling array $V_j$, fix $W_1, b_1$ of the first layer, with weight error ($\Delta w$) and bias error ($\Delta b$) initialize to zero.

(ii) For each OLI datasets one to nine (subscript marked with $j$), the hidden element vector $h_1$ is calculated, and the $W_k, b_k$, pre-training data of each RBM layer are fully trained from the original pixel value to the final class vector through the network feed forward.

(iii) The back propagation (BP) principle is used to calculate the reverse calculation gradient, update the learning parameter, and calculate loss value.

(iv) Adopt the Hessian matrix in Newton rapid iteration method and loop (i) to (iii) iteratively until root mean square error (RMSE) approaches the error threshold and loop exits.

The above completed DBN network training, inputs and outputs mapping. The feature vectors obtained by RBM through pre training are classified, and the parameters of the whole DBN network are fine tuned. When the error signal for each neuron is computed, the weights coefficients of each neuron input node will be modified. Running DBN in the OLI datasets, the target class pixel and non target class pixel are separated.

4. Experiments and analysis

4.1. Experiment data and results

Taking Anhui section of the Huaihe River Basin as the research area, LANDSAT8 image data (marked as LC81210372014297LGN00) with good quality (1.58% cloud) in 2014 was selected as the analysis object according to the research needs. The data came from the International Scientific Data Image of the Chinese Academy of Sciences (http://www.gscloud.cn/). 25 stable control points which are easy to be distinguished are collected by using the topographic map of the study area. According to the characteristics of land features, four secondary types (rivers, lakes, ponds and water plants, shown in Table 1) with similar characteristics were selected for information extraction and classification. The pre training samples were selected by visual interpreting of the image, combined with the field survey of GPS positioning sample points. Pre training data is used to train DBN model.

Table 1. Wetland types of interest in research area.

| Types      | Descriptions                                                |
|------------|-------------------------------------------------------------|
| Rivers     | Permanent or seasonal river, manually excavated main channel.|
| Lakes      | A still surface lake with an independent boundary.          |
| Ponds      | For farming, a reservoir, a impoundment area formed by barrages and dikes. |
| Water Plants | Water surface covered by aquatic plants.                    |

The DBN model is trained in advance by using the LANDSAT8 OLI data of the research area, it is concluded from the error statistics that the RMS error in the back propagation of the DBN model tends to converge after 200 iterations (Figure 4). The four types of wetland pixels are separated, and the natural distribution law of each type is obtained. Figure 4b shows that classification of rivers is the best, and there are obvious reclamation fields near the rivers and lakes, the shape features of reclamation lake boundary are also extracted by classifier.
4.2. Analysis and accuracy evaluation
In scene source image, 50 (50×4) test samples of each type of wetland are randomly selected. Combined with the high-resolution remote sensing image of Baidu satellite map and field survey data, the ground feature types of each sample point are determined by interpretation on the original OLI image. The confusion matrix, user accuracy and kappa coefficient of the four groups of classification results are calculated for accuracy evaluation.

Table 2. Classification statistics results.

| Types      | Area(km²) | User accuracy(%) | Kappa coefficient |
|------------|-----------|------------------|------------------|
| Rivers     | 10.603 8  | 98.45            | 0.956 0          |
| Lakes      | 27.346 5  | 96.69            | 0.933 4          |
| Ponds      | 17.238 6  | 94.79            | 0.912 5          |
| Water Plants | 27.007 2 | 87.21            | 0.857 9          |

Analysis experimental data in table 2, it can be seen that the classification effect meets the expectation. DBN model, after scale transformation of the sample, retained the useful information in the source image, get a high classification accuracy, while reducing the computational complexity. Activation of hidden layer feature vector is very conducive to OLI image classification. The spectral characteristics of roads in the source map are similar to those of ponds, that there is less sub-phenomenon mistake shows the good recognition ability of DBN model.

4.3. Discussion
For the OLI datasets, training samples should be selected based on high separation distance. The sample domain is often irregular shapes, and the number will be limited. When the number of training samples of input image is too small, the use of filter window will cause a lot of information loss in feature description. Adjusting the sample sampling scale can improve the effect of representative capacity.

The DBN model has some advantages for the feature learning task of remote sensing image. In this model, two hidden layer structures are designed, each RBM layer outputs feature mapping, and each element is obtained by calculating a training set. Then input the offset of the current layer connected to the feature map and the weight between the sets. For the terrain types with similar spectral features, the classification process of the OLI data can be completed. The experimental results show that, from a deep level, the extracted CNN features still retain a wealth of useful information, enough to describe the image. However, with the increase of the level and the training step, the over fitting phenomenon appears, which substantially reduces the model's ability to describe all datasets. The local minima of the network will lead to the failure of training.

5. Conclusions
The DBN model is comprehensively studied. Features of samples of the OLI datasets are transformed from the input space into the data correlation space, and the training process of the DBN model is tested. It is concluded that DBN has good recognition and image representation ability, and can well generalize the LandSAT8 OLI remote sensing datasets. The model is transferred to the near-spectrum
classification of four wetland types in the study area, the experimental results show that classification accuracy of rivers and lakes is at a high level, followed ponds and water plants, and the information and characteristics of each type are extracted to achieve expectations. In the next phase of the study, it is planned to study the spectral features of different bands in the LandSAT8 datasets, and label the image according to the feature semantics, thus simplifying the inputs of training data, reducing the DBN computational dimension and improving the classification efficiency.

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