CNN を利用した非都市地域における建物の抽出手法に関する研究

Identification of Buildings in Rural Environment based on Convolutional Neural Networks

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Abstract

Since accurate building maps are often unavailable or outdated in undeveloped rural environment, building identification in such areas has gradually become a significant research field in remote sensing. Due to the high price-performance ratio, many recent corresponding studies are performed based on open high-resolution remote sensing (HRRS) data such as Google Earth (GE) images. However, most existing classification methods applied for identification of building in rural environment identification can only generate low- or middle-level image features with limited representation ability, which essentially prevents them from achieving good performance in various scenes. Meanwhile, in image classification field, the preponderance of Convolutional Neural Network (CNN) [1] has been proved owing to its advantages such as efficiently generating high-dimensional abstract feature. In this dissertation, we present a specific CNN model which elaborately formulated based on state-of-the-art structures to identify buildings in rural environment from open HRRS images. First, the feasibility of proposed CNN based method is proven by comparing with other machine learning methods. Second, In order to optimize and mine CNN's capability for rural environment mapping and also be compatible with our classification targets, the basic model is carefully modified and adjusted based on a series of rigorous testing results. Third, the methods such as Transfer Learning, color balance and Data Augmentation are implemented to enhance the robustness of model. Finally, the generated model is applied in a pixel-level classification frame to generate high accuracy identification results. Experimental results of the test area at developing countries prove that the proposed CNN model significantly outperforms the previously best stated results, improving the overall accuracy from 96.30% to 99.26%, and Kappa from 0.56 to 0.86. For implementation on GPGPU and cuDNN, the required processing time accelerated approximately 30 times compared with CPU case.

1. Introduction

With the rapid development of urbanization processes, maps used to illustrate buildings and their distribution are significant and required in a wide range of fields. Important applications include environmental monitoring, resource management, disaster response, and homeland security. In urban areas, accurate maps are often available, but this is not always the case for rural environment. As an very important geoinformation, building maps are often insufficient, and there may be no digital version available. The deficiency building map information in rural environment would bring the inconvenience and several negative consequences.

Rather than fieldwork and ground investigation, identify buildings in rural environment depending on the remote sensing image would be more convenient and efficient. With the help of remote sensing satellite images earth-observation activities on regional to global scales can be implemented owing to advantages such as wide spatial coverage and high temporal resolution. A promising solution is offered by 3 bands high-resolution remote sensing (HRRS) images such as Google Earth (GE) and Bing Maps, which provides open, highly spatially resolved images suitable for building identification in rural environment.

In terms of classification technique, many methods have been studied by consulting published literatures. Note that the traditional visual interpretation of remote sensing images is a very complex and time-consuming process. In order to provide automatic and high accuracy identification result, with the help of image processing and feature extraction techniques, various machine learning algorithms such as Random Forest (RF) [2], Adaptive Boosting (AdaBoost) [3], Neural Networks (NN) [4] and Super Vector Machine (SVM) [5] in remote sensing have been implemented. However, most existing classification methods applied for rural environmental building identification can only generate low- or middle-level image features with limited representation ability, which essentially prevents them from achieving good performance in various scenes. Meanwhile, in image classification field, the preponderance of convolutional neural networks (CNN) has been proved in recent years owing to its advantages such as efficiently generating high-dimensional abstract feature.

To the best of our knowledge, there is no existing research by combining HRRS images and CNN to identify buildings only focusing on rural environment. Considering the characteristics of GE images and Bing Maps, we herein explore the feasibility of rural environmental building identification using CNN.

In this dissertation, we first constructed a basic four layer CNN to describe the characteristics inside an 18 x 18-pixel window and applied it to the identification. After analyzing the classification result, we modify CNN based on some state-of-the-art models and vigorous principles, and explore their potential in building identification respectively. Considering the limitation of available datasets, we also use data augmentation method to increase diversity and quantity of data. What's more, we utilize transfer learning in order to enhance our obtained models' capability, and some other image processing methods are also implemented as post processing in identification results.

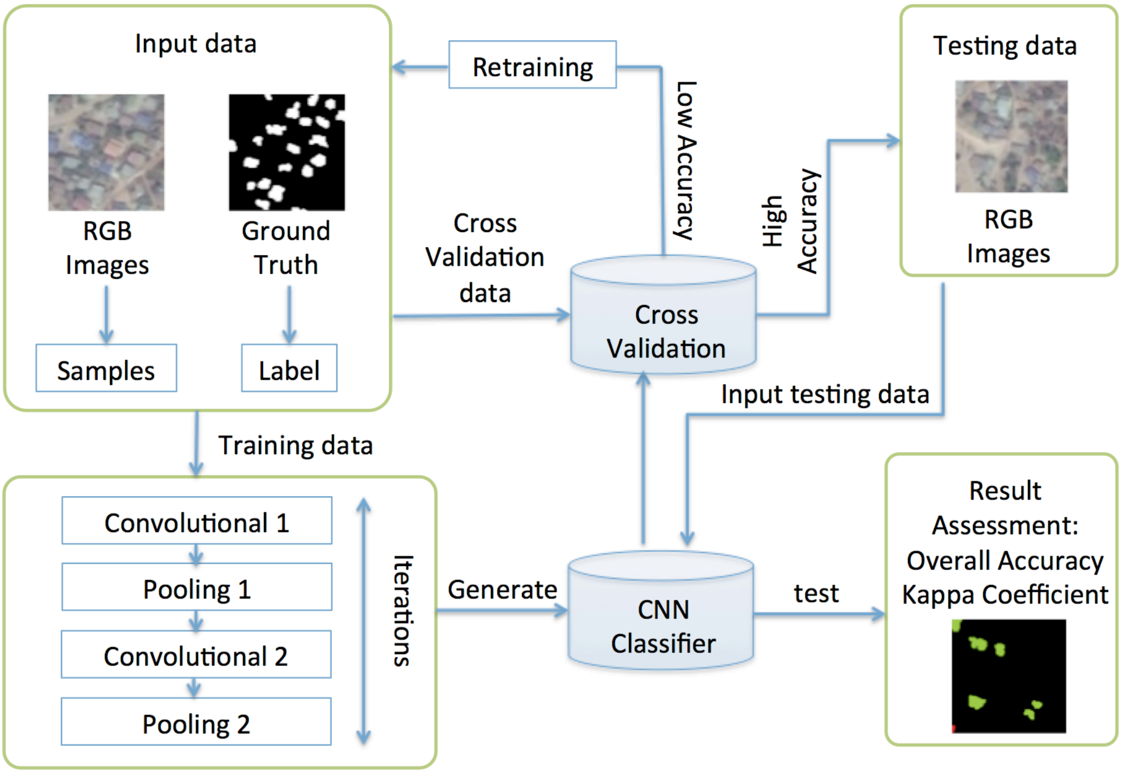

Figure 1. Approaches workflow

2. Approaches and workflow

An elaborate workflow (Figure 1) is formulated which mainly contains the flowing 6 parts:

- Training dataset preparation
- Model creation
- Model training
- Cross Validation
- Testing
- Post Processing

To conduct CNN, which is a supervised machine learning algorithm, preparing training samples and their relevant labels is the first step; then, rigorously elaborate CNN architecture in order to implement the training procedure; After training, the CNN classifier is generated; in order to verify the feasibility and stability of model, cross validation is implemented in the next step; then, the testing result and the corresponding figure will be generated by testing the provided dataset via obtained classifier. Finally, post processing is needed to improve result accuracy.

3. Results

In the outcome figure of CNN (Figure 2), gray refers to the unknown part, green means the actual buildings that were correctly classified as buildings, blue indicates the non-buildings that were incorrectly labeled as buildings, red shows the buildings that were incorrectly marked as non-buildings, and black denotes the correctly classified non-buildings. As shown in the result, our proposed CNN classifier has high performance in detecting

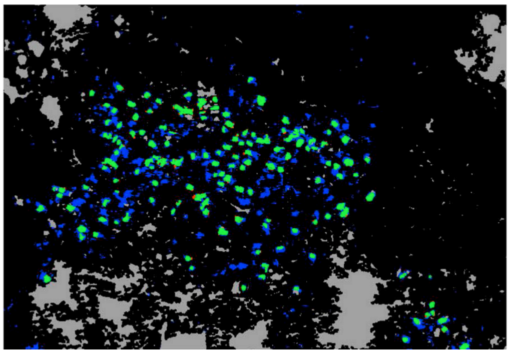

Figure 2. Testing results

buildings, which achieves an overall accuracy of 96.30% and Kappa 0.86.

4. Discussion

In this study, we propose a CNN based method for building identification based on HRRS images. The proposed method shows the ability of CNN in rural environment mapping, which is experimentally demonstrated by including several kinds of areas in rural environment. The obtained classifier can be used for all cases and no manual interaction is needed. Our method of CNN achieves a high accuracy, which is comparable to other methods. Furthermore, the proposed method can be efficiently utilized in remote sensing recognition of not merely buildings. Therefore, based on the result of this experiment, our proposed method is a promising approach that might be applied to many potential applications in the near future.

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