Multi-feature Fusion for High Resolution Aerial Scene Image Classification

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Abstract. Remote sensing scene classification plays an important role in many applications. Obtaining a high discriminative feature representation is the key of scene classification. The information hidden in different layers of convolutional neural network (CNN) has great potential for enhancing the feature discrimination ability. In this paper, the features from convolutional layers and a set of local features are combined for scene classification. Specifically, deep hierarchical features from different convolutional layers are extracted by a pretrained CNN model, which is used as a feature extractor. A patch-based MS-CLBP method is adopted to acquire local representations. Then the holistic hierarchical and local visual representation is obtained after fisher vector (FV) encoding. Finally, an improved extreme learning machine (ELM) is adopted to classify the scene images based on the obtained FVs. Experimental results show that the proposed methods achieves excellent performance compared with the state-of-the-art classification methods.

1. Introduction

With the development of remote sensing imaging techniques these years, overwhelming amounts of high resolution remote sensing (HRRS) images became available. It had widely applied to the field of forestry, city planning, land use/land cover (LULC) mapping and so on. HRRS scene classification aims to label the aerial images with the proper category automatically, i.e., distinguish different semantic categories by exploiting variations in spatial arrangements. Based on the discriminative features which are used for classification, there are three kinds of scene classification methods for HRRS: low-level handcraft features methods, mid-level visual representation methods, and high-level vision information methods.

Low-level handcraft features methods utilize the texture, structural and spectral features, etc., to distinguish aerial scenes. In the literature, researchers use local or global handcraft features, such as Scale-Invariant Feature Transform (SIFT) [1], local binary patterns (LBP) [2], color histogram and Global Invariant Scale Transform (GIST) [3] to describe aerial scene images. Mid-level visual representation approaches seek to express high-order statistical patterns of the extracted local visual attributes and obtain holistic scene representations for further classification. One of the most commonly used mid-level algorithms is Bag-of-Visual-Words (BoVW). BOVW model attempts to represent images by counting occurrences of the visual words, which are learned from the low-level features of images by a clustering method (such as K-means) [4]. One problem of BOVW in scene classification is that using only one visual word in K-means to approximate a local feature may lead to the reconstruction error. Several variants, such as sparse coding, linear locality-constrained coordinate
(LLC) and the Gaussian mixture model (GMM) [5] have been proposed for reducing reconstruction error of local features. Another mid-level feature coding method, the improved fisher kernel (IFK) [6], uses GMM rather than K-means to construct a dictionary, and represents an image by adopting the Fisher Vector (FV), which contain mean and covariance deviation information. The FV encoding models have shown good performance in HRRS scene classification [7-8], while the high-dimensionality of the mid-level feature vectors and lack of semantic information in features makes these models difficult to train on the large-scale datasets.

However, in recent years, advances in deep learning methods such as deep CNNs have shown the power of compact and discriminative representation and have demonstrated impressive performances on image classification. Thus a variety of CNN-based methods [9-13] has been proposed in the field of HRRS scene classification. These deep-learning based methods learn a robust holistic and hierarchical feature representation and perform well when the size of the training sample is sufficiently large.

Motivated by the success of multi-feature fusion and deep CNN models in the field of computer vision, in this paper, a novel multi-modality feature fusion framework for HRRS scene classification is proposed. More specifically, features from the immediate convolutional layers, which contain hierarchical structural information, are extracted and encoded into holistic semantic representations. Then a low-level feature method, i.e., patch-based MS-CLBP, is used to acquire local representations. Thus holistic hierarchical and local visual representations are obtained. Lastly, ELM is adopted to classify the scene image based on the FVs which are encoded from the multi-modality features.

There are two main contributions of this work. First, a novel multi-feature learning method using two different modalities of features including hierarchical and local features is proposed. Secondly, an improved ELM model is used to classify the holistic representations. The results on the public dataset have shown the superb performance of our proposed method.

2. Method Description
The flowchart of the proposed method is shown in Figure 1. First, multi-scale HRRS scene images are put into the pretrained CNN, the dense feature maps from different intermediate convolutional layers are extracted, and these dense feature maps can be considered as hierarchical meaningful representations. Then the patch-based MS-CLBP [14] is applied on the dense regions which are partitioned from the multi-scale HRRS scene images, and produce a set of local patch descriptors. Thus the high-level and low-level features from all of the training samples are used to train Gaussian Mixture Models (GMMs) respectively, and then they are encoded into discriminative meaningful representations (i.e., FVs) by the improved fisher kernel (IFK). Finally the FVs which are generated from the high-level and low-level features are concatenated, and put into ELM classifier for training and testing.

![Flowchart of the proposed method](image)

2.1 High-level and low-level features extraction and Fisher Kernel encoding
In previous studies, researchers have found that a typical CNN could extract hierarchical meaningful features on convolutional and full-connected layers when it is used as feature extractors. In this work, features from different convolutional layers of CNN are considered to be integrated for scene classification. To this end FV coding method is adopted to build mid-level features from convolutional layers. While Fisher kernel coding method is an out-of-order technique, scale phenomenon has great impact on the density distribution of the given image. In order to mitigate the impact of scale phenomenon, firstly a set of images at different scales by a pyramid algorithm [15] are generated, and then these images at different scales are fed into a pretrained CNN for to extract convolutional features.

Assuming the multi-scale convolutional features on \( i \) th layer of a given scene image \( I_s \) at scale level \( s \) as \( \{I^s_l\}_{l=0}^{p} \). Firstly the feature maps from \( i \) th convolutional layer are flatten into a set of feature vectors. Then each column of the feature set represents for a \( d \) -dimensional local descriptor which can be regarded as the feature representation of the corresponding image region. Thus \( i \) \( d \) -dimensional multi-scale features of \( i \) th convolutional layer are obtained for the image \( I_s \), which can be defined by

\[
F_\{i\} \{I^s_l\}_{l=0}^{p} = \{f_1^s, f_2^s, \ldots, f_p^s\} \in \mathbb{R}^d \tag{1}
\]

The local descriptor set \( F_\{i\} \) is high dimensional, thereby it is unpractical to directly use it as a feature. Here, IFK is used to aggregate these local descriptors into a compact feature vector. According to Ref. 6, given \( d \) training images the descriptor set \( F = \{F_1, F_2, \ldots, F_p\} \) are generated from \( i \) th convolutional layer. The descriptor set are used to fit the \( i \) th Gaussian mixture model \( GMM_i \). Then two \( d \) -dimensional gradients \( g_{\mu_i}^X \) and \( g_{\sigma_i}^X \) with respect to the mean and standard deviation, are utilized to build the FV representation. As a result, the linear vector representation of FV is obtained:

\[
\Phi_i (X) = \{g_{\mu_1}^X, g_{\sigma_1}^X, \ldots, g_{\mu_K}^X, g_{\sigma_K}^X\}^T \tag{2}
\]

Here, \( k \) is the component number of \( GMM_i \).

For the low-level features, the patch-based MS-CLBP [16] is considered. Firstly the MS-CLBP coded images are partitioned into \( B \times B \) overlapped patches. For each patch, the sign component and the magnitude component are extracted from each scale, and then combined together to obtain a MS-CLBP representation. For each CLBP parameter set, corresponding \( GMM_i \) is trained with feature matrices of the training data via EM. Finally, 300 dimension FVs as the descriptors [17] are obtained.

In our proposed feature fusion strategy, each test image \( x \) is encoded from two modalities of features. the features generated from high-level hierarchical meaningful feature and low-level patch-based MS-CLBP feature are denoted as \( F_\mu \) and \( F_\ell \), respectively. The feature-level fusion can be formulated as

\[
F(x) = \mu F_\mu(x) + (1 - \mu) F_\ell(x) \tag{3}
\]

where the feature \( F(x) \) is a final feature representation of test image \( x \). Settings of the weight \( \mu \) will be illustrated in the experimental section.

2.2 Classification by ELM classifier

Extreme learning machine (ELM) [18] is a single-hidden layer feed-forward neural network (SLFN). The parameters of the input weights and hidden layers biases in ELM are randomly assigned, and the output weights of SLFNs are determined analytically. The learning of ELM is simple and efficient because only the parameter of linearly connected weights should be tuned in the output layer. The training process needs to solve the least norm least-squares problem. Then We denote the equation

\[
N = \{(x_i, y_i) | i = 1, 2, \ldots, N; x_i \in \mathbb{R}^n, y_i \in \mathbb{R}^n\}
\]

to the training set of instance-label , and the output function of an SLFN with \( L \) hidden nodes can be written as
\[
\sum_{j=1}^{L} \beta_j f(o_{ij} x_i + b_j) = y_i, i = 1, 2, ..., N
\] (4)

Here, \(o_{ij}\) and \(\beta_j\) are all the weight vectors. \(o_{ij}\) connects the \(i\)th sample and the \(j\)th hidden node, while \(\beta_j\) connect the \(j\)th hidden node and the output nodes. \(b_j\) means the threshold of the \(j\)th hidden node. \(f(\cdot)\) is represented as the activation function. In order to train the SLFN, \(W, \beta, \hat{b}\) and \(\beta\) are obtained by:

\[
\|H(W, \hat{b}) \beta - T\| = \min_{\beta, b} \|H(W, b) \beta - T\|
\] (5)

The goal of Eq. (5) is to minimize the output error, which can be simplified as , where \(\beta = (\beta_1, \beta_2, ..., \beta_n)\), \(Y = (y_1, y_2, ..., y_n)\), and \(H\) is denoted as output matrix of the hidden layer. Eq. (5) represents a general linear system, and ELM minimizes the training errors by computing the corresponding least-squares solution \(\beta = H'Y = H'(HH')^{-1}Y\), where \(H'\) is the Moore-Penrose generalized inverse of hidden layer output matrix \(H\). In order to make the resulting solution of \(\beta\) to be more stable and have better generalization performance, inspired by Ref. 18-19 and ridge regression [20], a small positive value \(I/q\) is added to the diagonal of \(HH'\):

\[
\beta = H'(I/q + HH')^{-1}Y
\] (6)

Here, in the new feature space \(H\), the ELM output layer served as a linear solver. The output weights can only be adjusted in the ELM, and be solved analytically using ridge regression.

3. Experiment Setup and Result

In this work, a public HRRS dataset, UC-Merced (UCM) [21], is adopted to evaluate the performance of our proposed methods. Comprehensive experiment settings and evaluations are illustrated in this section. In the end, our method is compared with the state-of-the-art scene classification methods.

3.1 Dataset

The UCM dataset is the most widespread benchmark of HRRS scene classification. It has 21 distinctive scene classes, and each class contains 100 images with the pixel size of 256 × 256. Some highly overlapping classes (e.g. dense residential and medium residential) in the dataset share a few similar objects, thus the high inter-class similarity make the classification on UCM dataset challenging. Figure 2 shows some example images of UCM.

![Some examples from UCM dataset](image_url)

3.2 Experimental settings

For training set generation, a fixed ratio of training samples and total samples is adopted for each dataset. The dataset are randomly separated with the ratio of 80% on UCM for training, and left for testing. Our classification performance is evaluated with the average accuracy over 50 runs. VLFeat [22] are used for implementing the IFK coding methods. VGG-VD16 model which is pre-trained on Imagenet and available on the website: [https://github.com/BVLC/caffe/](https://github.com/BVLC/caffe/) is used to extract hierarchical features from convolutional layers. As mentioned in Ref. 23, features extracted from multi-scale input
image can enhance the classification performance. Multi-scale of $128 \times 128$ and the original $256 \times 256$ are set for the dataset. The number of Gaussian components in GMM which are used for encoding convolutional features and MS-CLBP are empirically set to be 100 and 16 respectively. As for the ELM classifier, the number of hidden nodes is the only parameter to be decided. Theoretically, the larger is the number of hidden nodes, the higher is the classification performance. Considering the balance of classification performance and computing cost, the number of hidden nodes is set to 6000 in the following experiments. Due to the fact that the high-level features do much more contributions to the classification than that of low-level features, then after a series of experimental evaluations, the high-level features are assigned with a relatively larger weight of 0.75. The learning epochs are 2000. The learning rate and the weight-decay are set to 0.1 and 0.0001 respectively.

3.3 Comparison with different classifiers
Classification performances of our proposed method with the classifiers of improved ELM, ELM and linear SVM [16,24] are compared. Figure 3 shows the detail of comparison. It can be observed that the performance of the proposed method + improved ELM overwhelms the proposed method + Linear SVM or proposed method + ELM. Even though the ratio of training sample is reduced to 20%, our proposed method + ELM could still achieve a pretty good performance. The good performance of proposed method makes it suitable for dealing with the dilemma of lack-of-sample in HRRS scene classification.

![Figure 3. Comparison of classification accuracies with SVM and ELM methods on the UCM dataset.](image)

3.4 Comparison with the state-of-the-arts methods
Table 1. Performance comparison of the state-of-the-art methods on the UCM dataset.

| Style name | Accuracy(%) |
|------------|-------------|
| SPM [17]   | 86.8        |
| Spatial BOW [21] | 81.19 |
| SC Pooling [25] | 81.67±1.23 |
| GBRCN [26] | 94.53       |
| SOS [27]   | 94.33       |
| salM3 LBP–CLM [28] | 95.75±0.80 |
| LGFBOVW [29] | 96.88±1.32 |
| GoogLeNet+fine-turning [30] | 97.1 |
| VGG-M+IFK [23] | 96.90±0.77 |
| Architecture(Ⅰ) [10] | 96.95 |
| GoogLeNet [31] | 94.31±0.89 |
| GoogLeNet fine-tuned [11] | 99.47±0.5 |
| VGG-S+VGG-VD16 [23] | 98.49 |
| VGG-VD16+Alexnet [15] | 98.81±0.38 |
To evaluate the performance of our proposed method, the performance comparison under the same experimental settings is shown on Table 1. From the table it can be seen that, our proposed methods outperform the mid-level feature encoding methods [17,21,25] and multi-feature fusion methods [27-29], which combine different modalities of features into the discriminative feature information to represent the scene categories for scene classification. Our results are also compared with the deep CNN-based methods which classify the scene images by the deep architecture of CNN [10,15,23,26,31] or the fine-tune approach [11,30]. Our proposed method (ELM) outperforms the most CNN-based methods except fine-tune approach [11] and combination of two deep CNNs [15]. Note that our proposed method just uses basic framework to directly transfer pre-trained deep CNNs for HRRS scene classification without using the fine-tune approach or complex combination of deep network. The fine-tuning is greatly influenced by the number of training images in HRRS dataset, and combination of two deep CNN is demanding on computing power and time consuming. In fact, our result on UCM dataset is very close to the performance of fine-tuning approach in Ref. 11 and multi-CNN combination approach in Ref. 15.

In addition, confusion matrix of our methods for the UCM data set is shown in Figure 4. As can be seen, most of scene categories on UCM achieve the accuracy close to or even equal to 1 by the proposed approach. Some kinds of HRRS scene are easy to be confused with other categories, such as dense resident and storage. The most confusing pairs are (dense residential, medium residential) and (dense residual, building), due to the similar spatial structures of these two scenes.

**Figure 4.** Confusion matrix of our method on UCM.

4. Conclusion
This paper presents a novel multi-feature fusion method for HRRS image scene classification. From this work it can be concluded that: (1) The combination of global features of the patch-based MS-CLBP and hierarchical features from intermediate convolutional layers contains rich and complementary information and shows the excellent classification performance. (2) Our proposed method with ELM classifier shows great power of classification, which is better than SVM, especially in the case that there are not enough training samples like in HRRS. In the future, two or more mid-level feature encoding methods (i.e., hierarchical encoding) can be used to encode the feature into more semantic visual representation, besides other appropriate low-level features can be incorporated in the combined features for classification.

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