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An improved LBP transfer learning for remote sensing object recognition

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ABSTRACT

In the object recognition process of the remote sensing image, as the object data is influenced by the imaging scale, intensity and the shape of the object, the distribution of the object data is very different with that of known training data which leads to the low reliability of the object recognition. Aimed at the problem, an object recognition method based on transfer learning framework for the remote sensing image is proposed in this paper. The feature vectors of the object data are extracted by an improved LBP firstly, and then the transfer learning is used to find the common parameters among the feature spaces of the object data with the different distributions. The transfer learning method can transfer knowledge from the old object data to the new object data and improve the performance of the object recognition. According to the experiments in the satellite remote sensing images, it shows that the accuracy of object recognition has been greatly improved by our proposed method compared with the other classical methods.

1. Introduction

Object recognition is one of the most important research topics in computer vision, image processing and machine learning. It has wide applications such as video surveillance, human computer, robots and so on. It is assumed that the object has been detected in the image, then learned and classified as one set of known labels. The main challenge in object recognition arises from the varying factors, such as shape, scaling, rotation, distortion and poses etc., and a successful recognition method should be robust to such changes. In the past decade, a variety of features and algorithms have been proposed and applied to this problem, resulting in significant progress in object recognition capabilities [1,2]. Object recognition has also been taken a great interest in remote sensing (RS). Since there are many applications in the RS image, the recognition rate become critical factor to these applications. Especially, such as some aircraft object, it is very hard for the computer to classify them correctly. It is difficult to recognize 3D object through 2D image. Different limited conditions of 3D object result great discrepancy in the 2D image.

Object recognition algorithm strategy basically grouped into two types: one is a bottom-up data-driven strategy, another strategy driven top-down knowledge. Early algorithm attempted on object recognition is focused on using geometric models, as the object's appearance is variable due to viewpoint and illumination change. Mundy research geometry-based object recognition in the excellent review [3]. In contrast to early efforts on geometry-based object recognition works, more recent efforts have been centered on appearance techniques as advanced features and pattern recognition algorithms are developed [4]. Adamek and O'Connor use curve contour for abstracting features [5], and Novotni use the features based on shape matching of 3D objects [6]. Classifiers such as K-nearest neighbor, neural networks with radial basis function (RBF), dynamic link architecture, Fisher linear discriminant, support vector machines (SVMs), and boosting algorithms have been applied to recognize 3D objects from 2D images [7].

More recently, Transfer learning has gained a great deal of attention due to its effectiveness to transfer informative knowledge from a source domain to a target domain with different distribution. It has become popular for a wide variety of applications [8–11]. Pan et al. divide the transfer learning methods into four categories in [12], that is, instance transfer [8], feature representation transfer [13], parameter transfer [14], and relational knowledge transfer [15]. Our transfer learning work is most related to relational knowledge transfer.

In this paper, we propose a novel object recognition method based on transfer learning frame for the RS image, as the distribution of the object domain data is very different with that of known training source data which leads to the low reliability of the object recognition. According to the characteristics of the RS image, firstly,

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the feature vector parameters of the object is used by an improved LBP, which provide object translation, scale and rotation invariance of 2D texture attribute. Then, we use a hybrid regularization framework to transfer knowledge from the old source data to the new domain data. Thus, the optimal classifier is chosen by learning the common parameters among the feature spaces of the object data with the different distributions, and it could improve the performance of the object recognition. The experimental results in the RS image, shows that the accuracy of object recognition has been greatly improved by our proposed method compared with the other classical methods.

The rest of the paper is organized as follows. In Section 2, we present the method of feature extraction. In Section 3, we introduce the transfer learning framework for object recognition. Experiments are shown in Section 4. And we conclude the paper in Section 5.

2. Feature extraction

Feature extraction is a first process in object recognition. The used feature belong to the object is represented as the small and effective feature vector. In the RS images, different types of ground objects have own specific texture attribute, such as, shape contour, length, width, area. So the texture attribute of the object is an important feature for object recognition. However, the texture feature is often affected by the imaging condition. So it is very necessary that the chosen feature can adapt the change of translation, rotation and scaling. The local binary pattern (LBP) [16] features have been used more widely due to the high performance and effective computation in recent years.

LBP characterizes the local structure of the texture image in a small circularly symmetric neighborhood that has Q equally spaced pixels on a circle of radius R. The values of the Q pixels are assigned to 0 when their intensity values are lower than the center's and 1 otherwise. And the LBP label of the center pixel is obtained by summing the Q binary values weighted with powers of two:

$$LBP_{Q,R} = \sum_{q=0}^{Q-1} s(g_q - g_c)2^p \tag{1}$$

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{2}$$

where g_q is the gray value of the pth sampling point and g_c is the gray value of the central pixel.

Especially, The LBP methods with the multi-resolution technique have shown good performances, such as the method of the rotation invariant uniform local binary pattern operator ($\mathrm{LBP}^{\mathrm{riu2}}$)[17]:

$$LBP_{q,R}^{riu2} = \begin{cases} \sum_{q=0}^{Q-1} s(g_q - g_c) & \text{if} \quad U(LBP_{Q,R}) \leq 2 \\ Q+1 & \text{otherwise} \end{cases} \tag{3}$$

where

$$U(LBP_{Q,R}) = \left| s(g_{Q-1} - g_c) - s(g_0 - g_c) \right| + \sum_{q=1}^{Q-1} \left| s(g_q - g_c) - s(g_{q-1} - g_c) \right| \tag{4}$$

According to Eq. (3), there are $Q+2$ output values in total. The histogram of LBP labels is computed to describe the texture. In order to enhance the performance, the multi-resolution technique is usually used. The multi-resolution technique concatenates the LBP histograms under different scales (Q,R) together to compute the (dis)similarity between a model and a sample.

Even so, the conventional LBP methods do not make the best of the patterns in different scales. These LBP methods have not considered the information among the patterns in different scales. The LBP methods in one scale just describe the simple structures of an image such as edge, spot, corner and so on. In this work, we combine local binary patterns under different scales together to describe the features of an aircraft object. Suppose the coordinates of a pixel are (x,y). The joint local binary pattern (JLBP) with two scales of the pixel (x,y) is defined as:

$$JLBP_{S_1,S_2}(x, y) = (LBP_{S_1}(x, y), LBP_{S_2}(x, y)) \tag{5}$$

where $S_1 = (Q1,R1)$ and $S_2 = (Q2,R2)$ stand for two groups of different scale parameters (Q,R). Similar, the rotation invariant uniform joint local binary pattern ($JLBP^{riu2}$) with two scales can be also defined as:

$$JLBP_{S_1,S_2}^{riu2}(x, y) = (LBP_{S_1}^{riu2}(x, y), LBP_{S_2}^{riu2}(x, y)) \tag{6}$$

3. RS object recognition based on transfer learning

3.1. Transfer knowledge

Traditional machine learning task is to learn given sufficient training data based on a classification model, and then take advantage of this learning model to classify and predict the test data. It gives an initial assumption that the training and test data should be under the same distribution. However, in many cases, this identical distribution assumption does not hold. While there are only few training data in the same distribution with the test data, classification might be poor. To maintain good classification performance, it is need to collect a large amount of the new training data to update the classification model for the test data. But, it would be very expensive to label the new data and also be a waste to throw away all the old training data. To reduce the effort for that learning task, we may want to adapt a classification model which is trained on the old training data to help improve classification for the new test data. Transfer learning method can try to transfer the knowledge from the source data to the target data when the latter has no or fewer high-quality training data.

In the RS image, as the detected object data are often different with the existing source data in the distribution of samples, it would be worse to identify the detected data through the classification trained by the existing data. We use the transfer learning method to find the similarity between the different distribution spaces of the training data and identification data, and transfer the knowledge from those data to improve the recognition results. Fig. 1 shows the similarity between the different types of aircraft, transfer learning

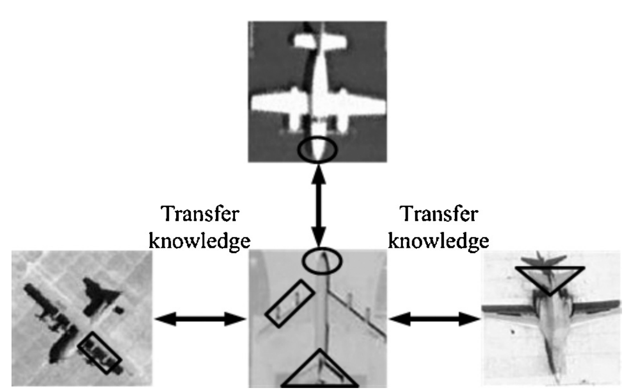


Fig. 1. Transfer similar knowledge.

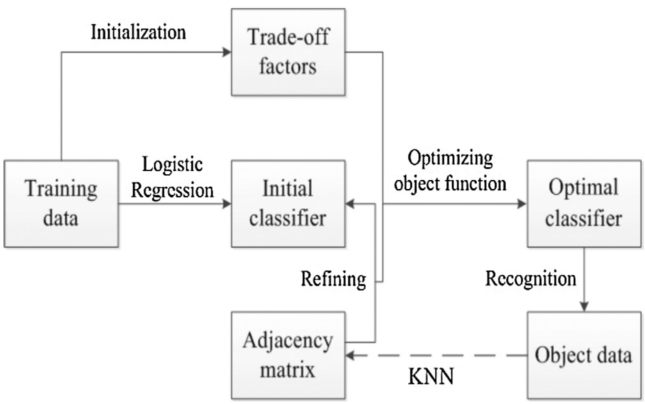


Fig. 2. The workflow of transfer knowledge framework.

method transfer the similar knowledge from some types of aircraft to help identify one type aircraft.

3.2. Transfer learning for object recognition

We propose a transfer learning framework for unlabeled objects to be detected and recognized in the RS images. Our transfer learning algorithm adapts a hybrid regularization framework to classify the objects. The hybrid regularization framework include manifold regularization [18] and entropy regularization [19]. Firstly, we learn a classifier h_s in the training data, which represents the source domain knowledge. Secondly, the hybrid regularization framework products an optimized classifier h_t through converging to a local optimum point combined with the classifier h_s. Finally, we use h_t to classify the object data, which represents the object domain knowledge different from the source domain knowledge in distribution. The workflow of the framework is shown in Fig. 2

In our case, we give a source training data set $D_s = \{x_i^s, y_i^s\}|_{i=1}^n$, where x_i^s is an sample (a feature vector computed for an RS object), $y_i^s \in \{-1, 1\}$ is a binary label, n is the number of the samples. We learn the classifier h_s on D_s by logistic regression [20], which learn optimized function by estimating its parameter from the training data. The classifier model is defined as follows:

$$P(y = \pm 1|x; w) = \sigma(yw^T x) = \frac{1}{1 + \exp(-yw^T x)} \tag{7}$$

where P is class-conditional probabilities expressed by the function σ, describing the distribution of the sample x feature vectors in each of the classes y, and w is the parameter of the model. After w is estimated under the Laplacian prior, the model can be used to compute the probabilities of the object belonging to the positive and negative class.

Then, we give the object domain data sets $D_t = \{x_i^t, y_i^t\}|_{i=1}^m$, where x_i^t is an sample which has been detected to recognize in the RS image, $y_i^t \in \{-1, 1\}$ is a binary label, m is the number of the samples. We refine the initial classifier h_s by the hybrid regularization framework on D_t. In the refinement process, we refine the model parameter w by minimizing the following objective function f:

$$f(w) = w^T w + \alpha_1 r_1 + \alpha_2 r_2 \tag{8}$$

where α_1, α_2 are trade-off factors among these regularization principles, and r_1, r_2 are manifold regularization and entropy regularization. Those regularizations have the good performance by transfer learning from the source data to object data. The regularizations are described as below.

3.2.1. Manifold regularization

It finds that the class of a sample be similar to the classes of its neighbors by the manifold regularization for learning. We apply it to the object domain for transfer learning, this regularization is to minimize the following formula:

$$r_1(w) = \frac{1}{m}\sum_{i=1}^{m}\left[\frac{1}{K}\sum_{k=1}^{K}\sigma(w^T x_{i_k}) - \sigma(w^T x_i)\right]^2 \tag{9}$$

where K is the number of sample x_i's neighbors, x_{i_k} is the kth $(1 \le k \le K)$ neighbor of sample x_i. The similarity relationship between x_i and x_j can be measured by cosine distance as follows:

$$\cos(x_i, x_j) = \frac{x_i^T x_j}{\|x_i\| \cdot \|x_j\|} \tag{10}$$

3.2.2. Entropy regularization

It is based on the fact that any sample belongs to only one class, and achieve a more reliable prediction of the classification by the entropy minimum on its true probability. As RS object recognition is the binary classification, the entropy regularization is equivalent to minimize the following formula:

$$r_2(w) = -\frac{1}{m}\sum_{i=1}^{m}\left[\sigma(w^T x_i) - \frac{1}{2}\right]^2 \tag{11}$$

To solve the optimization problem of object function f, we compute the partial differential of r_1, r_2 as follows:

$$\begin{aligned}\nabla_w r_1 = {} & \frac{2}{m}\sum_{i=1}^{m}\left(\frac{1}{K}\sum_{k=1}^{K}\sigma(w^T x_{i_k}) - \sigma(w^T x_i)\right) \times \\ & \left(\frac{1}{K}\sum_{k=1}^{K}\sigma(w^T x_{i_k})(1-\sigma(w^T x_{i_k}))x_{i_k} - \right. \\ & \left. \sigma(w^T x_i)(1-\sigma(w^T x_i))x_i\right)\end{aligned} \tag{12}$$

$$\nabla_w r_2 = -\frac{2}{m}\sum_{i=1}^{m}\left(\sigma(w^T x_i) - \frac{1}{2}\right)\sigma(w^T x_i)(1-\sigma(w^T x_i))x_i \tag{13}$$

Thus, the partial differential of function f is shown as below:

$$\nabla_w f = 2w + \alpha_1 \cdot \nabla_w r_1 + \alpha_2 \cdot \nabla_w r_2 \tag{14}$$

We can use conjugate gradient method to solve the optimization problem, which obtaining the local optimum based on the initial model h_s.

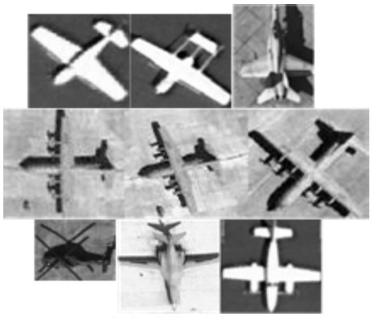
Finally, we use the optimal classifier ht to recognize the objects in the RS images.

4. Experiments

4.1. Experimental setup

In our experiments, we test our transfer knowledge algorithm on object recognition of the RS images, which are collected from Internet. Training positive samples are comprised of 100 aircraft samples. The positive samples with different types, variant translation, rotation and scaling, are chosen randomly by the training set every time. Training negative samples are comprised of 100 non-aircraft samples with different types, such as mountain, road, cars, buildings and so on. Test samples are comprised of 100 other types of aircraft samples chosen randomly by the object set every time. The aircraft samples belong to the object set have been detected in the RS images. The distribution of the training samples is different from that of the object samples. The samples are showed in Fig. 3.

To demonstrate the performance of our transfer learning framework, in the feature, we compared our JLBP against conventional



(a) Training samples

(b) Object samples recognized in the RS images

Fig. 3. The RS samples.

Table 1
Comparison of methods for RS aircraft recogniton.

Methods	Accuracy (%)
SVM (JLBP)	78.7
K-NN (JLBP)	74.3
BPNN (JLBP)	85.3
Proposed algorithm (LBP)	85.8
Proposed algorithm ($LBP^{riu2}_{Q,R}$)	89.6
Proposed algorithm (JLBP)	92.2

LBP: LBP, $LBP^{riu2}_{Q,R}$. Meanwhile, under the chosen JLBP feature, we compared our transfer learning methods against the classic classifier methods, such as, Support Vector Machines (SVMs), K-Nearest Neighborhood (K-NN) and Back Propagation Neural Network (BPNN).

4.2. Experimental results

Here we present the ability of our approach to effectively transfer knowledge between different types of aircraft objects. The performance in recognition accuracy rate is the average of 10 repeats by random. The trade-off factors α_1, α_2 are set to 0.4, 15. From Table 1 we find that the proposed JLBP feature method can raises the transfer learning classification accuracy by 6.4%, 2.6%, comparing with the basic LBP, LBP^{riu2}. And our transfer learning method also obtains better results than other three classification methods on the JLBG feature. Transfer learning with JLBG can achieve a high recognition accuracy, which reach 92.2%. The accuracy is improve 6.9% when compared with the second in the BPNN method. The comparison results demonstrate that our approach can transfer the useful knowledge from the different types of RS aircraft data to help the learner for object recognition, when there is no or too few same type of training aircraft data to train a good classifier. It shows that our transfer learning approach with JLBG can reduce the effects of the variant translation, rotation and scaling and has greatly improved the performance of object recognition in the RS images.

5. Conclusion

In this paper we introduce propose transfers learning framework for object recognition in the RS images, while there is no enough same type of existed samples to train a good classifier for the unidentified objects, the recognition reliability is very low. The novel approach use transfer learning with a improve LBP to find the common parameters among the feature spaces of the object data with the different distributions, and transfer knowledge from the old object data to the new object data to build a good robust classifier. Experimental results on the RS objects have shown that our approach can improve the performance of recognition.

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