Remote Sensing Image Analysis Based on Transfer Learning: A Survey

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Abstract. Transfer learning is a new topic in machine learning. Psychology holds that the process of learning knowledge from one to the other is a process of transfer learning. Transfer learning is different from machine learning which has to satisfy the following two conditions: (1) The training samples and testing samples must be in the same feature spaces. (2) There must be enough training samples to obtain an excellent training model. Because of the ability of transfer learning to solve problems with small samples and the ability to use historical auxiliary models to solve new problems, it is introduced in remote sensing image analysis. At first, this paper introduces some basic knowledge of transfer learning and enumerates some basic research examples. The research content of this paper mainly involves several problems based on transfer learning, such as target detection and recognition, image classification, etc.

Keywords: Transfer learning · Remote sensing image · Target detection · Target recognition · Image classification

1 Introduction

With the improvement of satellite remote sensing image resolution, there is more information that is useful in remote sensing image. More and more occasions require remote - sensing information, such as precise missile research, marine condition monitoring and other military systems as well as emergency management of natural disasters, traffic supervision and other civilian systems [1]. Meanwhile, many sensors produce a great quantity of multi-scale remote sensing images, such as visible light, infrared light, hyperspectral imager, radar and so on. The result is a big increase in data, even explosive growth. Different image information is required for different applications, such as target detection, image classification and target recognition et al., which brings new challenges for remote sensing image analysis.

Transfer learning is a method of applying knowledge learned from one or more source domains to a different but related target domain. It can solve new research problems with historical auxiliary data [2]. The purpose of transfer learning is to apply available data to less labeled datasets or even unlabeled datasets, which can effectively

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solve the case of fewer labeled samples in new tasks. The center of this theory is to find similarities between domains. One of the biggest problems in remote sensing image processing is the inability to quickly acquire a large number of accurate labeled sample data. At the same time, the existing algorithms cannot recycle the historical data effectively, which leads to the waste of historical data. It is worthwhile to note that the part that can be improved by transfer learning is exactly the problem to be solved in the process of remote sensing image analysis.

2 Transfer Learning

The researchers showed that, unlike similar previous studies, transfer learning is not limited by the assumptions of traditional machine learning (ML). It eases two basic suppositions in traditional ML: (1) The training and testing samples must be in the same feature spaces. (2) There must be enough training samples to obtain an excellent training model. Transfer learning can solve problems in different but related fields using available knowledge, and it will be the next driver of machine learning (ML) success.

The most authoritative article about transfer learning is “A Survey on Transfer Learning [3]” by Prof. Yang. Since then, researchers follow awfully with interest transfer learning. Its application is not limited to specific fields [26]. Transfer learning can play a role in many areas [27] which include, but are not limited to, computer vision, text classification, behavior recognition, natural language processing, indoor positioning, video surveillance, etc.

According to whether the feature space is the same, transfer learning (TL) is divided into homogeneous TL and heterogeneous TL [4]. According to whether the sample is marked, transfer learning consist of inductive TL, transductive TL and unsupervised TL. Furthermore, the more common classification method is divided into four categories according to literature [3]: instance-based transfer learning, feature-based transfer learning, parameter-based transfer learning and relational transfer learning.

2.1 Instance-Based Transfer Learning

The instance-based transfer learning is redistributing the weight of samples according to a certain rule. Sample weighting and importance sampling are the main research contents. How to select training samples that are beneficial to target tasks is a problem to be solved by instance-transfer. The common method is increasing the weights of samples with high similarity.

During the process of research, many scholars set the direction as estimating the probability density ratio between the two research domains, that is, estimating instance weight. One of the classical algorithms is TrAdaboost, proposed by Dai, which is based on Adaboost [5]. It assignments different weights to the training samples through different mechanisms, increasing the instance weights that are conducive to target classification task, and reducing the instance weights that are not conducive to classification task. Based on PCA theory, the upper bound of generalization error of the model is derived. In addition, Tan et al. proposed a transitive transfer learning (TTL), which utilizes joint matrix decomposition [6]. The purpose of this method is to realize the knowledge transfer when the source domain and the target domain share a handful of knowledge.

In general, instance-based transfer learning is a relatively basic method, which is usually more suitable for the case where the distributions difference between domains are small. Therefore, the application scope is limited.

2.2 Feature-Based Transfer Learning

Feature-based transfer learning means the effective feature representation through feature selection or feature transformation. And then the use of these features is transfer. The most classical algorithm is the Transfer Component Analysis (TCA), which is proposed by Pan in 2011 [7]. The following is a brief introduction to the TCA algorithm.

TCA first assumes that the marginal probability distributions of two domains are diverse. Pan believed that there is a feature transformation method, which makes the probability distributions consistent after transforming.

Maximum Mean Difference (MMD) was selected as a distance measure.

$$\text{Distance}(X_s, X_t) = \left\| \frac{1}{n_\text{s}} \sum_{i=1}^{n_\text{s}} \Phi(\text{X}_i) - \frac{1}{n_t} \sum_{j=1}^{n_t} \Phi(\text{X}_j) \right\|_\text{H} \tag{1}$$

TCA introduces the nuclear matrix K and MMD matrix L,

$$K = \begin{bmatrix} K_{s,s} & K_{s,t} \\ K_{t,s} & K_{t,t} \end{bmatrix} \tag{2}$$

$$l_{i,j} = \begin{cases} \frac{1}{n_1^2} & \text{X}_i, \text{X}]_j \in D_s \\ \frac{1}{n_2^2} & \text{X}_i, \text{X}_j \in D_t \\ -\frac{1}{n_1 n_2} & \text{otherwise} \end{cases} \tag{3}$$

Formula (4) presents the $\text{Distance}(X_s, X_t)$,

$$trace(\text{KL}) - \lambda trace(\text{K}) \tag{4}$$

Then, the formula (5) is obtained by dimensionality reduction,

$$\widetilde{K} = (\text{KK}^{-1/2}\widetilde{W})(\widetilde{W^T}K^{-1/2}K) = \text{KWW}^T K \tag{5}$$

W is what we want. The traditional machine learning method can be applied on the reduced dimension data of two domains.

Many excellent feature selection algorithms have been proposed. Structural Correspondence Learning (SCL) algorithm represents implicit feature mapping based on semi-supervised multitasking learning [8]. Transfer Joint Matching (TJM) algorithm selects adaptive marginal probability distributions and source sample selection in optimization target [9]. The algorithm combines feature with instance transfer learning method. Gu [10] et al. researched several related clustering tasks and proposed a framework of shared feature subspaces in which all domains share clustering centers. The subspace method in the feature transformation has achieved superior results.

2.3 Parameter-Based Transfer Learning

Parameter-based transfer learning usually aims at finding shared parameters from both source and target domains. Long improved the deep network structure and added the probability distribution adaptation layer to the deep network, which further improved the generalization ability of the model [11–13].

Some of the researchers improved and transferred SVM model. Nater [14] considered the weight vector W of SVM as a combination of two parts:

$$W = W_0 + V \tag{6}$$

Where W_0 represents the common part of two domains, V represents particular parts of two domains.

At present, most parameter based transfer learning are combined with deep neural networks, which achieve excellent results.

2.4 Relational Transfer Learning

Relational transfer learning is quite different from above approaches. This method focuses on the relationship between source samples and target samples. For example, Mihalkova used Markov logical networks to mine the similarities between domains [15]. Generally speaking there are few researches on this method and it is still at the basic stage.

3 Target Detection Based on Transfer Learning

Target detection in remote sensing images corresponds to the problem of face detection in natural images, that is, detecting the existence of the target in a certain scene. The targets being detected are generally summarized in the following three categories: Linear targets such as airstrips, roads and rivers; Block target such as airplanes, tanks and ships; Complex targets such as airports, ports and bridges.

As one of the methods used in machine learning to solve the problem of domain adaptation, transfer learning has also achieved good results in remote sensing image target detection. Xu applied the idea of transfer learning to airport detection [16]. The author used Faster R-CNN as the basic framework and used the RPN network to generate candidate regions. In order to transfer the common features, the parameters of the lower convolution layers in the pre-training model keep constant or overlapped at a small learning rate in the new task. The reason is that the lower convolution layers in the CNN learn low-level semantic features. In this paper, the problem of data type imbalance is solved by the method of difficult sample mining. It accurately detected different types of airports in complex background. Researchers state this method is superior to others, and it has strong theoretical and practical significance for real-time airports detection.

Chen [17] proposed an end-to-end detection model for aircraft detection in complex background, which is based on transferring deep CNN. In this model, the two-stage task of classification and localization is combined into one problem. The framework in natural images, YOLO, is used to detect aircraft in remote sensing images. The framework is widely used in other target detection tasks, which is block target similar to aircraft.

4 Target Recognition Based on Transfer Learning

Target recognition is analogous to the task of face recognition. We usually give an initial assumption that the object has been detected in the image before recognition. And giving the types of targets is what we are required to accomplish.

The earliest target recognition method is template-matching theory. After that, the model-based approach is widely studied. It extracts features from the original high - resolution images and abstracts the target into an object model, a background model or an environment model for recognition [28].

In the case of enemy Unmanned Aerial Vehicle (UAV) accuracy improvement of recognition and classification, Xie [18] proposed a Sparse Auto-Encoder (SAE) algorithm based on transfer learning. Four parts are formed to achieve the algorithm, that is, sampling and preprocessing module, source feature training module, target domain global feature extraction module and target classification module. Firstly, unsupervised learning of unlabeled samples in source domain is carried out, and local features are obtained. Then, CNN with pool layer is used to extract the global features of tagged images in target domain. Finally, the classification part uses the softmax regression model. The proposed SAE algorithm based on transfer learning can be applied on small sample multi-frame enemy UAV images.

Lima used fine-tuning for the first time in ocean front recognition [19]. It provides a new direction for further research. Li applies DNNs to SAR automatic recognition technology and uses AdaGrad (Adaptive Subgradient Methods) instead of SGD (Stochastic Gradient Descent) as the weight optimization function [20]. Based on transfer learning theory, an improved network structure is proposed to recognition SAR. Experimental results show that the theory can improve the training process of network parameters and improve the accurate rate. ZP Dan proposed a transfer model on the base of LBP feature, which is able to detect and recognize unlabeled samples in remote sensing images [21]. The LBP algorithm is used to extract the eigenvector of the target domain. The mixed regularization framework, including manifold regularization and entropy regularization, realizes transfer process. A better robust classifier is trained by common parameters found in the feature space of different target data.

5 Image Classification Based on Transfer Learning

Scene classification is an important step in remote sensing image processing. In order to analyze and manage remote sensing image data effectively, it is necessary to attach semantic labels to the images according to their contents, and scene classification is an important way to solve this problem [29]. Scene classification is to distinguish images with similar scene characteristics from multiple images and classify these images correctly.

Li proposed a method based on CNN Inception-v3 model to solve the problem of lacking labeled sample in scene classification of remote sensing images [22]. Feature vectors of the sample are extracted by pre-training model. The feature extraction is carried out by using pre-training weight rather than training the weight parameters of inception-v3, which is more efficient than the traditional method of feature extraction. After that, the vector is input into a single-layer fully connected neural network including Softmax classifier. Higher classification accuracy results are obtained and demonstrated with a small number of labeled remote sensing images.

Literature [23] proposed a new heterogeneous transfer framework for hyperspectral image classification, IRHTL. IRHTL algorithm first iterated to learn the projection of two domains. The next step is reweighting the source samples and increasing the proportion of useful samples. Finally, the classifier of the target domain is successfully obtained. Heterogeneity solves the problem of inconsistent feature space of remote sensing information from different sensors. This algorithm promotes remote sensing image processing to some extent.

Xia et al. of the Tokyo University improved TCA algorithm. They proposed E-TCA algorithm, which is used to solve the problem of domain adaptive in hyperspectral remote sensing image classification [24]. E-TCA successfully embodies the superiorities of integrated learning and TCA. In this paper, they selected RF (Random Forest) to predict the labels of target images. It has been proven that the new algorithm is better than the traditional TCA and RF.

Xu proposed domain adaptation with parameter transfer (DAPT) on the base of Extreme Learning Machine (ELM) algorithm [25]. The new idea transforms the ELM parameters of the target domain back to the source domain, and it selected BoVW feature and deep features which can represent the image well. Moreover, the author avoids the negative transfer by regularization constraint.

6 Conclusion

With the development of transfer learning, there will be more effective methods for remote sensing image analysis. The survey mainly investigates the research of remote sensing images based on transfer learning in recent years. It summarizes the techniques of transfer applied to target detection, target recognition and image classification. It can be seen that transfer learning in remote sensing images analysis is reasonable and practicable, it is worthy extending. However, since there are still some problems in the field of transfer learning, there are still many unknown remote sensing transfer algorithms worth studying.

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