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Semi-Supervised Learning for the Classification of Remote Sensing Images: A Literature Review

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Abstract—*Classification of remote sensing images is a challenging task due to various constraints presents in the remote sensing areas. Availability of the labeled data set is a one of the biggest problem in the area of remote sensing. The collection of the labeled data set is very tedious, expensive and time consuming task. Supervised classification techniques do not perform well due to limited availability of labeled training samples. To solve the problem of limited training samples in the remote sensing areas many semi-supervised techniques have been explored and developed in last ten years. In this paper, the semi-supervised techniques which are explored and developed for the classification of the remote sensing images are reviewed.*

1. INTRODUCTION

Remote sensing is a science and art to capture data and information of any object or geographic location through a sensor device that is very far from that device [1]. It has many applications in different areas like vegetation assessment, land cover detection, change detection over area, agricultural monitoring, glacier monitoring, forest burned area identification, urban and rural area monitoring and environment change study etc[2]. Due to advancement in the sensor technology, it has been become very easy to capture very large amount of data with different scales every day. It is impossible to extract useful information from these large amounts of captured data through human analysis in real time. Due to this reason, it is required to develop computational based information extraction techniques for the remote sensing data. The remote sensing data have many challenges like spatial relationship, high dimensionality, overlapping nature of concepts and classes, limited number of labeled samples, large data size, temporal relationship, noisy data etc. [3-4]. These all challenges add various difficulties to the machine learning and remote sensing community in the development of data analysis techniques for the remote sensing images [5-6]. The machine learning leaning community has developed a lot of data analytics techniques to extract meaning full information from the data sets. These techniques have been applied and explored in many ways to extract meaning full information from remote sensing images. Classification techniques plays very important role to extract useful information from remote sensing images. Unsupervised, supervised and semi-supervised are the three main categories in the classification techniques. All three categories have been explored and used for the classification of the remote sensing images in different situations and environments [7].

Supervised classification techniques require large amount of label data to train a classifier and accuracy of these techniques depend on the availability of large and heathy labeled samples [8]. On the other hand, the unsupervised techniques try to cluster similar objects in same group in the absence of labeled data [9]. Unsupervised classification technique do not require any labeled information due to this reason, accuracy of these techniques are not happens to be good in many situations. In the area of the remote sensing, it is very hard and expensive to collect labeled samples. To solve this problem, many semi-supervised classification techniques have explored and developed for the remote sensing images in the recent years. Semi-supervised techniques require a very few amount of labeled samples and a large amount of unlabeled samples to train a classifier system [10]. Graph based semi-supervised techniques, classifier objective function modification based semi-supervised techniques and self-labeled based semi-supervised techniques are the three main categories in semi-supervised technique.

In graph based semi supervised techniques, the unlabeled and labeled samples are assumed to be graph nodes and weights among nodes are calculated by using any similarity measurement based methods [11-12]. The objective function is used to design on the constructed graph by assuming different criteria and constraints. The solutions of the objective function assign the label to the unlabeled samples.

In the second the category of the semi-supervised techniques, the objective function of the traditional classifier like support vector machine (SVM)[13-14], neural network [15-17] and classifier based on the generative methods[18-19] are used to modified to include the information of unlabeled and labeled samples. For the remote sensing images, SVM classifier has achieved good classification accuracy. Due to this reason, SVM has modified in many ways to include unlabeled samples for the semi-supervised classification of remote sensing images.

The third category of the semi supervised technique is self-labeled technique which is used to train the supervised classifier or set of classifiers in iterative manner without modifying their objective functions. Self-training [20], co-training [21] and committee based semi- supervised techniques [22] are the main self-label semi supervised techniques. In this category of semi supervised techniques, the most confident samples are used to include in labeled data pool in several iterations. These techniques are wrapping in nature, it means that any classifier can be integrated in to the framework [23-24]. In recent years, graph based semi-supervised techniques, semi-supervised techniques based on the support vector machine (SVM) and self-labeled based semi-supervised techniques are mainly explored for the classification of the remote sensing images. In this paper, above semi-supervised techniques are reviewed and year wise study of the algorithm have been presented for the classification of the sensing images.

2. SEMI-SUPERVISED LEARNING FOR REMOTE SENSING IMAGES

Learning with both labeled and unlabeled samples is called semi-supervised learning. In this technique, a classifier model is developed with limited number of labeled and a large set of unlabeled samples. Graph based semi-supervised techniques, semi-supervised techniques based on the SVM and self-labeled semi-supervised techniques are widely explored for the classification of the remote sensing images.

2.1 Graph Based Semi-Supervised Techniques

In graph, the nodes connected through height weight are assumed to share same class. The properties of the graph have been utilized to design many graph based semi-supervised learning techniques. In graph based semi-supervised techniques, the graph is constructed through labeled and unlabeled samples and the edge weights are calculated among nodes of the graph through any distance based metric. Machine learning and data mining community have developed various graph based semi-supervised techniques. These techniques have been utilized in many ways to classify remote sensing images. Gustavo Camps-Vallshave et al. have proposed a graph based semi-supervised method for hyperspectral remote sensing images which handles high dimensionality, few labeled samples and spatial characteristics of the pixels. The method tried to make graph based on composite spatial and spectral kernels [25]. Yanfeng Gu, Kai Feng have proposed a semi-supervised method for classification of the remote sensing images based on the L1 graph. The authors claimed that the proposed method is more robust, parameter free and sparse handling capability than traditional graph based semi-supervised technique [26]. Jun Bai, Shiming Xiang, and Chunhong Pan have applied a graph cut minimization to classify the hyperspectral remote sensing images. The method is designed for label problem for Markov random field [27]. Yue Gao et al. have discovered a bilayer graph based technique for the classification of the remote sensing with limited number of labeled samples. In this method, the authors created the graph in two steps firstly a simple graph based on pixel similarity and then second layer graph based on the similarity of the group of the pixels [28]. Rongrong Ji, Richang Hong, Qiong Liu, Dacheng Tao, and Xuelong Lihave have developed a graph based semi supervised techniques based on the spatial and spectral characteristics of the hyperspectral remote sensing images. The proposed method construct hyper graphs among pixels and weight among pixels are calculated with spatial and spectral criteria. The proposed method is robust than other state-of-the-art methods [29]. Wang, Liguo, et al have developed a method which utilize spatial and spectral information to construct the graph and the constructed graph is used to propagate label samples. After minimizing the energy graph the prediction of unlabeled samples are made which are used to train SVM classifiers [30]. Ma, Li, et al have proposed a method which uses manifold learning to construct the graph for semi-supervised classification of the remote sensing images. The local geometric properties can be capture by utilizing local manifold learning [31].Ma, Li, Andong Ma, Cai Ju, and Xingmei Li have designed a spatial-spectral regularized based graph semi-supervised techniques for the classification of remote sensing images. For the spectral regularization, sum of minimum distance are used to determine neighborhood relationship and to determine edge weight local manifold learning is used [32].

2.2 Semi-Supervised SVM

Semi-supervised SVM is explored and modified in many ways for the classification of the remote sensing images. In the most of the semi-supervised SVM, the objective function is designed such as it maximize the margin with help of labeled and unlabeled samples while keeping labeled samples correctly classified. Chi, Mingmin, and Lorenzo Bruzzone have developed a semi-supervised SVM which utilize both labeled and unlabeled samples to construct SVM boundary. The addition of unlabeled samples regularization terms makes SVM objective function as a nonconvex optimization problem. The author solved this problem in primal and results show that the proposed method is better than dual implementation for the semi-supervised classification of the remote sensing images [33-34].Gomez-Chova, Luis, et al have developed a Laplacian SVM for the semi- supervised classification of the remote sensing images. In this method a graph based regularization terms are added in traditional support vector machine objective function to utilize information of unlabeled samples [35]. Tuia, Devis, and Gustavo Camps-Valls. have proposed a semi-supervised method which uses cluster kernel to utilize unlabeled samples information. This technique is different than above other technique which uses a composite kernel based on the actual features kernel and a clustering based kernel [36]. Marconcini, Mattia, Gustavo Camps-Valls, and Lorenzo Bruzzone have applied composite kernel based semi-supervised SVM for the classification of the remote sensing images. This method utilizes spatial and spectral relationship with composite kernel and to avoid few labels problem the unlabeled samples are used [37]. Muñoz-Marí, Jordi, et al have proposed a semi-supervised SVM for the classification of one class remote sensing data [38].Gómez-Chova, Luis, et al have proposed a semi- supervised SVM method which utilize unlabeled samples through cluster kernel technique. The means map kernel methods are used to construct final kernel matrix for the traditional SVM model[39].Tuia, Devis, and Gustavo Camps-Valls have proposed a semi supervised SVM based on the multi scale cluster kernels. The proposed method combines both labeled and unlabeled samples information through linear combination of kernels. The unlabeled samples information is extracted through cluster kernel method [40]. Ul Haq, Qazi Sami, et al. have developed a fast and robust sparse approach for classification of remote sensing images with few labeled samples. "The authors try to exploit certain special properties of hyperspectral data and propose an l-1-minimization-based sparse representation classification approach to overcome this difficulty in hyperspectral data classification"[41]. Gu, Yanfeng, and Kai Feng have proposed a modified laplacian SVM with distance metric for the semi-supervised classification of the hyperspectral images. The traditional laplacian SVM add an additional regularization term for graph laplacian. The traditional method has been modified by including distance metric to calculate weight instead of Euclidian distance [42].Tan, Kun, et al. have proposed a semi-supervised based SVM with segmentation based ensemble for the hyperspectral remote sensing image classification. In proposed method segmentation techniques are used to enlarge the label data set [43]. Yang, Lixia, et al. have proposed a spatial-spectral laplacian SVM for the semi supervised classification of Hyperspectral Remote sensing images. The clustering criteria in spectral domain is used to create spatial regularizer and neighborhood relationship are used to create spectral regularizer [44].Huo, Lian-Zhi, Ping Tang et al. have proposed semi- supervised SVM based on the segmentation kernel and cluster kernel. The proposed method used hierarchical spatial similarity and clustering technique to compute cluster kernel. The finally composite kernel is used to train SVM for the classification of remote sensing images [45].

2.3 Self-Labeled Semi-Supervised Techniques

Self-labeled techniques are the semi-supervised techniques in which a classifier or a set of classifiers are trained in iterative manner with the help of limited number of labeled and a pool of unlabeled samples. Self-training, co-training and committee based self-labeled techniques are the three main categories of the self-labeled semi-supervised techniques. These techniques are applied in many ways for the classification of remote sensing images. Bruzzone, Lorenzo, Mingmin Chi, and Mattia Marconcini have proposed a method to train SVM in self-training fashion. A threshold has designed for SVM to select moderate informative samples for the training of SVM classifier in iterative manner. The method is successfully applied on remote sensing images for the semi-supervised classification [46]. Maulik, Ujjwal, and Debasis Chakraborty have proposed a self-training ensemble method for the semi supervised classification of remote sensing images. The proposed method trains ensemble of the SVM in self-training fashion [47]. Liu, Y.et al. have developed a method to train a SVM classifier in self-training framework with boundary samples. The boundary samples are assumed to informative samples for the SVM classifier. On selected boundary samples the filtering process are applied with Gustafson–Kessel fuzzy clustering algorithm to select the corrected classified samples [48]. Maulik, Ujjwal, and Debasis Chakraborty have proposed a method to train SVM in self-training manner for semi supervised classification of remote sensing images. They have shown that the result can be validated without having any label data with the help of fuzzy c-means [49]. Dópido et al have proposed a self-training approach by exploring neighboring pixels of hyperspectral remote sensing images. They have created pseudo label set by selecting neighboring pixels of highly confidently classified pixels. The authors have used active learning approach to select informative samples from pseudo label set [50]. Zhang, et al has proposed co-training based self-labeled semi-supervised techniques for the classification hyperspectral remote sensing images. The authors have used spectral features as a first view and extracted spatial features as second view for co-training process. They have also designed new samples selection straetegy for the co-training semi-supervised techniques [51].Tan, Kun, Jun Hu, Jun Li, and Peijun Du. have proposed a method in which combination of classifiers are trained in self-learning fashion. They have used spatial neighborhood information from remote sensing images and those pseudo label pixels are utilized to train combination of classifier in iterative manner [52]. Aydav, Prem Shankar Singh, and Sonajharia Minz have used self-training approach for the spatial-spectral classification of remote sensing images which takes help of clustering techniques to train the supervised classifier in self-training manner [53]. Aydav, Prem Shankar Singh, and Sonajharia Minz have proposed technique which selects the informative samples by using a threshold to train a supervised classifier in self-training fashion. The techniques take help of clustering techniques to filter the informative samples to improve the reliability of their classification label [54]. Tan, Kun, Jishuai Zhu, Qian Du, Lixin Wu, and Peijun Du have proposed a tri-training semi- supervised self-labeled semi-supervised technique for the classification of hyperspectral remote sensing images. The algorithm uses diversity measure criteria to select optimal label set for classifiers [55]. Aydav, Prem Shankar Singh, and Sonajharia Minz have proposed a co-training approach which uses semi supervised fuzzy C-means and SVM on the spatial and spectral view of the hyperspectral remote sensing images[56]. Lu, Xiaochen, Junping Zhang, Tong Li, and Ye Zhang have proposed a self-training method which first segment the high resolution remote sensing images and uses active leaning concepts with diversity measurement to select most confident as well as the informative samples[57].

3. CONCLUSIONS AND FUTURE DIRECTIONS

Semi supervised classification techniques play very important role in the knowledge extraction from remote sensing images. It is very costly and time consuming to collect the labeled data sets in the area of remote sensing and sometimes also impossible. On the other hand, unlabeled data are easily available. So, it has become necessary to develop classification techniques which utilize very less labeled data and pool of unlabeled data. In this paper, the semi supervised techniques which are specially designed and explored for the classification of the remote sensing images in recent years are reviewed

In future, SVM can be modified such that its objective function includes both unlabeled information as well as the spatial information. The objective function design should be such that it does not come under nonlinear optimization problems. Also the optimization techniques should be developed to handle nonlinearity of the semi supervised SVM machine. The self-labeled techniques are very flexible semi supervised techniques. In the future, the self-labeled techniques should be modified in such way that it includes confident as well as informative samples. In self-labeled semi-supervised techniques the active learning concepts may be integrated in the future to select optimal labeled data sets. Graph based semi supervised techniques have provided good results on the small data sets but on the on the large data sets performance decreases. In future, there is need to develop graph based semi-supervised techniques for large size of the remote sensing images.

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