SEMI-SUPERVISED HIGH-RESOLUTION IMAGE CLASSIFICATION USING CRF MODEL

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ABSTRACT

Images which is of high resolution have the type of plentiful statistical and detail information, which are useful for detailed classification. The predictable algorithm combine spectral cues, spatial contextual cues and spatial location cues by using probabilistic potentials. By using equivalent potentials the split trainings of easy classifier is well applied. Experiments Hyper-spectral images display well-built depen- dencies diagonally spatial and spectral neighbours, which are very helpful for classification of hyper spectral image. High-resolution images have the type of abundant statistical and feature information, which are helpful for detailed classification. By using probabilistic potentials the classification algorithm which is based on conditional random fields(CRF) is existing algorithm merge spectral cues, spatial contextual cues and spatial location cues. The unary potentials used on spectral cues and give the basic information about various land-cover classes. The pair- wise potentials applied on spatial contextual cues, it deals with the neighbouring connections between different pixels to deal with spatial smoothing. The higher order potentials deals with the spatial location cues. The target pixel and its nearest training samples interacts in higher order potentials which consider the non local range of spatial location. Useful information is provided for the classes that is similar to the other land-cover types which confused with the other classes of spectral appearance. The CRFSS algorithm add spectral cues, spatial contextual cues and spatial location cues in a CRF framework to offer contradictory in sequence from changing perspectives, so in remote sensing images it address the common problem of spectral variability , so because of this classes of each class and the average accuracy is reflected.

Keywords: Conditional Random Fields, Detail preserving smoothing classifier, Markov random field, Support vector machines.

I. INTRODUCTION

In remote sensing, main undertaking is land-cover classification. Hyper-spectral image classification has a demanding focus of land-cover classification investigate because hyper- spectral image include rich spectral quality, the categorization, identification and classification is done of land -covers which increase accuracy and robustness [1]. To each pixel in an image a predefined semantic labelling is done in classification. This procedure is also known as semantic segmentation. the different sensor platforms (such as IKONOS, Quick-

Bird, and ROSIS) can provide profuse available data for accurate earth observation of high-resolution images. urban planning, precision agriculture, security applications, and damage assessment for environmental disasters these are the application domain of high- resolution remote sensing imagery.

A huge amount of images for various thematic applications are available for functioning imaging system.

1. Ecological science: To study land cover vary or to approximation biomass, biodiversity are used in Hyper-spectral and spatial images.

2. Geological science: Properties such as composition and abundance are used to recover physiochemical mineral.

3. Hydrological science: To resolve changes in wetland characteristics is used in Hyper-spectral and spatial imagery.

4. Precision agriculture: To classify agricultural classes and to remove nitrogen content in Hyper-spectral and spatial data for the point of precision agriculture[5].

5. Military applications: For objective detection the rich spectral spatial information is used.

To improve the performance of classification and to make full use of the spatial information and spectral-spatial classification many researchers have complete deal of endeavour. For spectral-spatial classification the probabilistic modeling methods have successfully used. And the probability map is first obtained by pixel-wise classification. Probabilistic modeling methods represents each land cover classes by each pixel. To consider the spatial information the probability map is use of local filtering or extended random walker method [3]. To implement smoothness in object-oriented classification method the another obvious way to regard the spatial information. The goal of spectral spatial classification the main object oriented classification approach is to merge the classification and segmentation algorithms. In segmentation, divide the image into homogeneous objects and then calculation of majority voting strategy is applied on the basis of pixel-wise classification or direct classification and this is used to give the labels of various land cover classes, taking objects as the basic unit.

II. REVIEW OF LITERATURE

A detailed Literature survey[14] conducted by analyzing adequate papers on Image Processing which helps in developing a new hyper-spectral image classification algorithm is based on the discriminative conditional random fields (CRFs) to the same time deal with the problems mentioned previously.

Mathieu Fauvel, Yuliya Tarabalka et all in their paper entitled Advances in Spectral-Spatial Classification of Hyper-spectral Images focused spectral spatial classification of hyper-spectral images is addressed. Morphological profile of the image, which contain characteristics about the size of the image, orientation, and contrast of the spatial structures present in the image is first used to derive in mathematical morphology. To derive additional features for classification are defined and used in the morphological neighbourhood. SVM which is used to avail the spectral information and the extracted spatial information through that the classification is performed [2].

Gabriele Moser, Sebastiano B. Serpico, et all in their paper entitled Land-Cover Mapping by Markov Modeling of Spatial Contextual Information in Very-High-Resolution Remote Sensing Images focused on the role of

spatial- contextual information in the discrimination of land-cover classes has allowing for the Markovian, region-based, and texture based approaches to the modeling of this information in land-cover classification techniques. Examples of processing results is obtained by classical and advanced Markovian classifiers in the application, presenting diverse types of land covers and of spatial image behaviours [3].

Donald Geman ,Stuart Geman , et all in their paper entitled Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images focused the role of Gibbs distribution, Markov random field (MRF) correspondence it converse the energy usefulness is a more fitting and natural mechanism for represent picture feature than the local characteristics of the MRF. For a variety of squalor mechanisms, with blurring, nonlinear deformations, and multiplicative or preservative noise, the subsequent distribution is an MRF with a structure similar to the image model[4].

Farid Melgani, Lorenzo Bruzzone , et all in their paper entitled Classification of Hyper-spectral Remote Sensing Images With Support Vector Machines focused the role of Hyper-spectral Remote Sensing Images, attend to the problem of the classification of hyper-spectral remote sensing data using support vector machines. In order to consider the competence of accomplished classification methodology. This aimed at assessing the properties of SVMs in hyper-dimensional spaces and hyper-subspaces of various dimensionalities [5].

Vladimir Kolmogorov, Aseem Agarwala, Daniel Scharstein, Olga Veksler, Marshall Tappen and Carsten Rother, et all in their paper entitled A Comparative Study of Energy Minimization Methods for Markov Random Fields with Smoothness-Based Priors focused the role of Markov Random Fields where the increase of proficient energy minimization algorithms for pixel-labeling responsibilities such as depth or texture calculation is done. Algorithms such as graph cuts and loopy belief propagation (LBP) have established to be very established. For example, such technique form the base generally all the top-performing stereo methods. Here, represent a set of energy minimization benchmarks and use to evaluate the result excellence and runtime of some common energy minimization algorithms[6].

Runsheng Wang, Ping Zhong, et all in their paper entitled Learning Conditional Random Fields for Classification of Hyper-spectral Images focused the role of Hyper-spectral images where Hyper-spectral images reveal well-built dependencies across spatial and spectral neighbours, which have been establish to useful for hyper-spectral image classification. Over-smoothing and over fitting are the essential methods used to categorize the hyper-spectral images using conditional random fields [7].

Jocelyn Chanussot, Jn Atli Benediktsson, Yuliya Tarabalka, Mathieu Fauvel, et all in their paper entitled SVM and MRF Based Method for Accurate Classification of Hyper- spectral Images focused the role of Accurate classification which current new challenges to image investigation and classification refer the high number of spectral bands obtain by hyper-spectral sensors enlarge the potential to discriminate corporeal materials and objects, presenting new challenges to image analysis and classification[8].

Runsheng Wang, Ping Zhong, et all in their paper entitled Modeling and Classifying Hyper-spectral Imagery by CRFs With Sparse Higher Order Potentials focused on the role of Sparse higher order potentials which have been proved to be very helpful for hyper-spectral image classification, which expose the well-built dependencies across spatial and spectral neighbours. Here, based on the CRF model it overcome the control of hyper spectral

image classification with sparse higher order potentials, which are mainly considered to merge complex characteristics of hyper-spectral images [9].

Xiuping Jia , Guangyun Zhang et all in their paper entitled Simplified Conditional Random Fields With Class Boundary Constraint for Spectral-Spatial Base-Remote Sensing Image Classification focused on the role of Class boundary constraint using Conditional random fields (CRF) to unite contextual information into remote sensing classification which introduced to remote sensing image classification .In the experimental results the advantages of the developed method are established using real remotely sensed data [10].

Konrad Schindler et all in their paper entitled An Overview and Comparison of Smooth Labeling Methods for Land-Cover Classification focused the role of smooth category methods in the inequity of land-cover classes which assess that all methods previously over smooth when most capable, pointing out that there is require to include more and more complicated prior information into the classification process [11].

Liangpei Zhang , Yanfei Zhong, Xuemei Lin, et all in their paper entitled A Support Vector Conditional Random Fields Classifier With a Mahalanobis Distance Boundary Constraint for High Spatial Resolution Remote Sensing Imagery focused on the role of Mahalanobis distance boundary constraint is planned to perform the undertaking for high spatial resolution (HSR) remote sensing imagery of classification [12].

Liangpei Zhang , Ji Zhao, Yanfei Zhong, et all in their paper entitled Detail-Preserving Smoothing Classifier Based on Conditional Random Fields for High Spatial Resolution Remote Sensing Imagery focused the role of HSR imagery is planned to apply the object-oriented strategy to Detail preserving smoothing classifier based on conditional random fields (DPSCRF) in the CRF classification framework, thus combining the merits of both approaches to believe the spatial contextual information and preserve the detail information in the classification[13].

After reading and analyzing detailed survey, a new system of semi-supervised learning classification of CRFSS algorithm using different potentials and merging spectral cues, spatial contextual cues and spatial location cues is suggested through this paper.

III. PROPOSED SYSTEM

3.1 Problem Statement

By combining the spectral cues, spatial contextual cues and spatial location cues for high resolution images to improve the effect of spectral variability using conditional random fields classification using Semi-supervised approach.

3.2 System Architecture

Unary, pair-wise and higher order potentials are used by the spectral cues, spatial contextual cues, and spatial location cues respectively in the CRFSS algorithm. To recover the classification performance together they can afford opposite information from altering perspective.
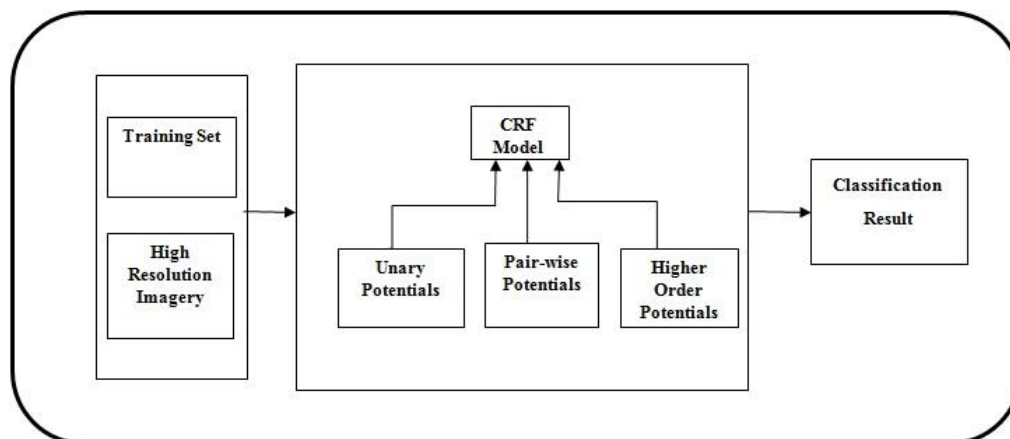
Fig.1. Flowchart of conditional random field classification algorithm combining spectral cues , spatial contextual cues, and spatial location cues (CRFSS).

The CRFSS algorithm is illustrate in state as follows.

1. By the location information the nonlocal similarity of the land-cover type are used to maintain the stability of the image in spatial location cues. The spatial location cues are directly mould by higher-order potentials. In remote sensing image classification, which show the scenarios of same material with different spectra and similar spectra from different materials in remote sensing images have the spectral variability which have a significant influence. Based on the spatial dependency principle this occurrence is not likely to happen in a local region [1].

Therefore, in spatial location cues the local regions are used to improve the result of spectral variability. The higher order potentials it consider the non local range of interactions between the target pixel and the nearest training samples for all classes, it based on the spectral similarity of same land cover classes of local region. It also deals with the spatial location cues are changed from the spatial information which is used in spectral-spatial classification algorithms.

2. The spectral and spatial location perspective it helps to improve the misclassification caused by the spectral correspondence in remote sensing high resolution images, the spectral and spatial location cues afford the opposite information of the land cover type. The CRFSS algorithm which is used in spectral and spatial location cues include the class membership probabilities. In the unary potentials the spectral cues formulated class membership probabilities. The higher order potentials deals with the spatial location cues and it give more useful information for different classes. And these classes are easily confused with the land cover types, which determine the class membership probabilities as of an additional point of view. So, all the potentials functions are integrated in the CRFSS classification algorithm based on the class membership probabilities [7].

3. To take the spatial contextual information into account the CRFSS algorithm take over the advantages of the CRF mode, which is mould by pair-wise potentials to consider the spatial connections of neighbouring pixels. To defeat salt-and-pepper classification noise and gain a reasonable classification by the α-expansion

presumption algorithm. The depiction of the potential functions in CRFSS to believe the spectral cues, spatial location cues and spatial contextual cues information, conclusion by the graph-cut based -expansion algorithm is achieve to predict the optimal labelling by reduce the energy function.

Due to the limitation of the size of the cliques the pair-wise CRF model has the complexity of capturing wide range spatial contextual information. To labelling problem the richer spatial connections are more beneficial for accurate model to advance the performance of the model, this measured by the higher order potentials in CRF model. Multiple random variables are cliques in higher order potentials, so this has the higher modeling power. The CRF model with higher order potentials is also called as higher-order CRF.

IV. SYSTEM ANALYSIS

To consider the spatial contextual cues information and to improve the spectral variability the CRFSS algorithm is proposed. The CRFSS algorithm consist the spectral cues, the spatial contextual cues information, and the spatial location cues with using different potentials [5]. Collectively, it can give corresponding information about different land cover classes from various perspective, and it can help to improve the contact of spectral variability of remote sensing image classification to advance the performance.

1. Unary Potentials

    For single image site the unary potentials are used to model and categorize observations. The observed spectral values are used to show the complex information and it cannot be fully form of Gaussian distributions for the task of hyper-spectral image classification. The unary potential is low in case of equivalent pixel individual accurately classified with a high degree of assurance [8]. The land cover class label of pixel is usually reduces the energy when the assurance of pixel of taking class label is high. The penalization is occur in unary potentials and is high when the pixel is misclassified.

2. Pair-wise Potential

    Based on the spectral cues information of pixels and segmentation are independently performed in a pixel wise classification. The SVM pixel wise classifier technique is used to efficiently handles the hyper spectral data. While segmentation of region all the pixels are assigned to most frequent class in the region. To deal with pair-wise potentials mainly focus is on ability to set contextual information. By considering the previous analysis about contextual information of hyper spectral image, it seems that with the high probability it assumes that neighbouring sites will be from same land cover type. By considering the labelling field and observation field the pair wise potential models give the spatial contextual information between each pixel.

3. Higher-Order Potentials

    Higher order cliques are the energy minimization based method. It is used to solve the problems that assume the energy represent in terms of unary and pair wise potentials. To unable capture the rich statistic of natural scenes assumes that restricts the representation power of these models .The complex interactions of random variables has the capability in higher order cliques [9].

4.1 Limitations

1. High resolutionary images only used to perform the classification.

2. The dataset should be trained partially before performing the classification of high resolution images.

3. While capturing the high resolution images using satellite then the images affected by cloud coverage.

4. And images acquire clearly during day time.

V. EXPERIMENTAL SETUP AND RESULTS

5.1 Experimental Setup

The Pavia Center ROSIS (Reflective Optics System Imaging Spectrometer) Dataset captures a different urban images. This is urban image has spatial resolution of 1.3m and the size of spatial image is 1096 by 715 pixels. In this 102 bands are used in spectral image [1].

5.2 Results

These results contain the dataset of ROSIS sensor and has the accuracies like Overall accuracy and Average accuracy. These accuracies are in percentage form. SVM, SVRFMC, DPSCRF, CRFSS (Supervised) all these are previous algorithms which contain different technique of classification. And in addition to that CRFSS (Semi- supervised) algorithm is implemented and the Overall accuracy and Average accuracy are measured in this paper as shown in Table I.

TABLE I

ACCURACIES FOR THE PAVIA CENTER ROSIS DATASET

Methods	Overall Accuracy(%)	Average Accuracy(%)
SVM	97.51	94.77
SVRFMC	99.08	97.73
DPSCRF	99.37	98.18
CRFSS(Supervised)	99.78	99.52
CRFSS(Semi-Supervised)	99.82	99.68

These are the graphical representation of Overall Accuracy and Average Accuracy. Different previous techniques are shown such as SVM, SVRFMC, DPSCRF, CRFSS (Supervised) and the technique which is implemented in this paper is CRFSS (Semi-supervised). This is the graph of Overall accuracy, here by the comparison of all previous techniques CRFSS (Semi-supervised) algorithm has the highest overall accuracy. CRFSS (Supervised) and CRFSS (Semi-supervised) algorithms has very less difference in accuracies.
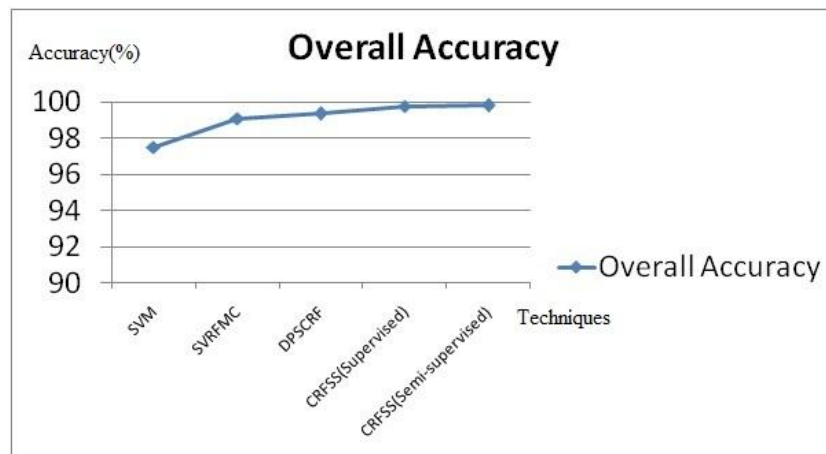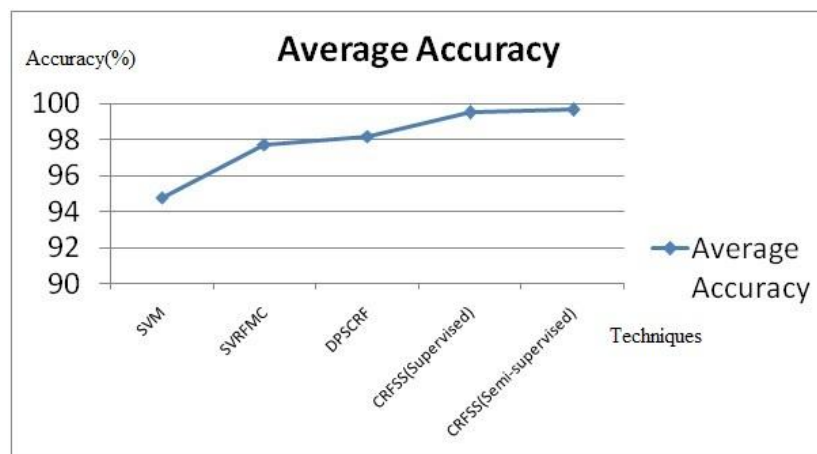
Fig. 2. Overall Accuracy

Fig. 3. Average Accuracy

This is the graph of Average accuracy, here by the comparison of all previous techniques CRFSS (Semi-supervised) algorithm has the highest average accuracy. CRFSS (Supervised) and CRFSS (Semi-supervised) algorithms has very less difference in accuracies.

VI. CONCLUSION

In this paper, the process is to integrate spectral cues, spatial contextual cues and spatial location cues of high resolution images using conditional random fields (CRFSS). Each cues has it's different focus and provide complementary information of pixel label about land cover classes. It improve the classification of spectral variability with the help of unified probabilistic CRF framework. Probabilistic CRF framework contains different potentials like unary, pair-wise and higher order potentials, each potential has different focus and perspective. So, it leads to improve the misclassification occur because of spectral variability. With these three potentials classification improve by combining spectral, spatial contextual and spatial location cues.

VII. ACKNOWLEDGMENT

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