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Image Classification-Review

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Abstract— **Hyper-spectral images display strong dependencies across spatial and spectral neighbors', which have been proved to be very helpful for hyper-spectral image classification. High-resolution images have the type of plentiful geometric and detail information, which are useful to detailed classification. The predictable algorithm integrates spectral, spatial contextual and spatial location cues by modeling the probabilistic potentials. It is well implemented through split trainings of easy classifiers defined by equivalent potentials. Experiments Hyper-spectral images display strong dependencies across spatial and spectral neighbors, which have been proved to be very helpful for hyper-spectral image classification. High-resolution images have the type of plentiful geometric and detail information, which are useful to detailed classification [13].**

Experiments on real-world hyper-spectral data illustrate that algorithm is reasonable with the most current results in hyper-spectral image classification. The projected algorithm integrates spectral, spatial contextual, and spatial location cues within a CRF framework to give matching information from changing perspectives, so that it can deal with the common problem of spectral inconsistency in remote sensing images, which is directly reflected in the accuracy of each class and the average accuracy. The new results with three high-resolution images prove the validity of the algorithm, compared with the other state-of-the-art classification algorithms [6].

***Index Terms*— Conditional random fields, Markov random field, Support vector machines.**

I. Introduction

In field of remote sensing, main task is land-cover classification. Hyper-spectral image classification has being a exacting focus of land-cover classification investigate because hyper-spectral image contains very rich spectral attributes, which allows the categorization, identification and classification of the land-covers with better accuracy and robustness.

We are performing strong literature survey which helps in developing a new hyper-spectral image classification algorithm based on discriminative conditional random fields (CRFs) to at the same time deal with the problems mentioned previously.

- First, as a discriminative method, CRF directly models the posterior as Gibbs distribution, and then it avoids the problem of clear modeling of likelihood. Thus, CRF can be simply used to categorize various hyper-spectral images, no matter what distributions follow. The altered data of a variety of hyper-spectral images are captured by supervised learning and denoted in variety of different learned parameters of CRF model.
- Second, as well avoiding of clear modeling of likelihood, CRF has intrinsic skill to include the contextual information in both label and observed images in a righteous manner. The contextual information is captured through intrinsic CRF structure, not require of difficult modeling of the dependencies among interpretation of neighboring sites. After the modeling method, the problem remains is functioning of CRF training. Correct view is difficult in general because the partition function of Gibbs distribution depends not only upon model parameters but also on input data [13]. This means the limit estimation requires computing partition function for each training case and also in every iteration of a numerical optimization algorithm. Since CRFs for image investigation are large graphical models with loops, the computing can be costly. To deal with this problem, a variety of approximate methods have been used in parameter view. In hyper-spectral and spatial image classification, the most usual job is to choose some samples from a particular image for classifier training, and then the learned classifier is used to classify the remaining test samples in the similar given image. So limited training methods should be used equivalent to the task of hyper-spectral and spatial image classification [6].

CRF has the essential ability to integrate the contextual information in both the labels and observed data. Thus, for the first issue, we focal point on defining CRF graph construction to extend a new hyper-spectral and spatial image classification algorithm [8].

Many functioning imaging systems are now available providing a huge amount of images for various thematic applications.

- Ecological science: Hyper-spectral and spatial images are used to approximation biomass, biodiversity, or to study land cover changes.
- Geological science: It is probable to recover physiochemical mineral properties such as composition and abundance.
- Hydrological science: Hyper-spectral and spatial imagery is used to resolve changes in wetland characteristics. Water quality, estuarine environments, and coastal zones can be analyzed as well.

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- Precision agriculture: Hyper-spectral and spatial data are used to classify agricultural classes and to remove nitrogen content for the point of precision agriculture
- Military applications: The rich spectral spatial information can be used for objective detection.

II. Literature Survey

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. Taking into account the need of spatial information during the classification process and the number of spectral components, several approaches were considered. The framework of the proposed methods can be summed up as extraction of spatial and spectral information and the combination of information either during the classification step or after a primary classification. Several techniques are investigated for combining both spatial and spectral information. Spatial information is extracted at the object (set of pixels) level rather than at the conventional pixel level. Mathematical morphology is first used to derive the morphological profile of the image, which includes characteristics about the size, orientation, and contrast of the spatial structures present in the image. Then, the morphological neighborhood is defined and used to derive additional features for classification. Classification is performed with support vector machines (SVMs) using the available spectral information and the extracted spatial information. Spatial post processing is next investigated to build more homogeneous and spatially consistent thematic maps [01].

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 the role of spatial–contextual information in the discrimination of land-cover classes has been discussed by considering the Markovian, region-based, and texture based approaches to the modeling of this information in land-cover classification techniques. Examples of processing results obtained by classical and advanced Markovian classifiers in the application to two case studies, presenting diverse types of land covers and of spatial image behaviors, have been presented and discussed. Markov models represent a wide and general family of stochastic models for the temporal and spatial dependence properties associated to 1-D and multidimensional random sequences or random fields. Their applications range over a wide variety of subareas of the information and communication technology (ICT) field, including networking, automation, speech processing, genomic-sequence analysis, or image processing. Focusing on the applicative problem of land-cover mapping from very-high-resolution (VHR) remote sensing images, which is a relevant problem in many applications of environmental monitoring and natural resource exploitation [02].

Stuart Geman , Donald 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) equivalence it discussed the energy utility is a more suitable and natural mechanism for embodying picture attributes than the local characteristics of the MRF. For a range of squalor mechanisms, including blurring, nonlinear deformations, and multiplicative or additive noise, the posterior distribution is an MRF with a structure similar to the image model. By the similarity, the posterior distribution defines another (imaginary) physical system. Steady temperature diminution in the physical system isolates low energy states ("annealing"), or what is the same thing, the most probable states under the Gibbs distribution. The equivalent operation under the posterior distribution yields the maximum a posterior (MAP) approximate of the image given the tainted observations. The result is a highly parallel "relaxation" algorithm for MAP inference. Establish union properties of the algorithm and experiment with some simple pictures, for which good restorations are obtained at low signal-to-noise ratios [03].

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, addressed the problem of the classification of hyper-spectral remote sensing data using support vector machines. In order to assess the efficiency of capable classification methodology, here considered two main objectives. The first was aimed at assessing the properties of SVMs in hyper-dimensional spaces and hyper-subspaces of various dimensionalities. The results obtained on the consider dataset allow to identify the following three properties [4]:

1)SVMs are much more useful than other conventional nonparametric classifiers in terms of classification accuracy, computational time, and stability to parameter setting;

2) SVMs seem more efficient than the traditional pattern recognition approach, which is based on the combination of a feature extraction/selection process and a conventional classifier

3) SVMs exhibit low sensitivity to the Hughes phenomenon, resulting in an exceptional approach to avoid the usually time-consuming phase required by any feature-reduction method [4].

Richard Szeliski, Ramin Zabih, Daniel Scharstein, Olga Veksler, Vladimir Kolmogorov, Aseem Agarwala, 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 expansion of efficient energy minimization algorithms for pixel-labeling tasks such as depth or texture computation is done. Algorithms such as graph cuts and loopy belief propagation (LBP) have verified to be very prevailing. For example, such methods form the basis for roughly all the top-performing stereo methods. Here, depict a set of energy minimization benchmarks and use them to compare the result quality and runtime of some common energy minimization algorithms. Investigate three promising recent methods—graph cuts, LBP, and tree-re weighted message passing—in addition to the well-known older iterated conditional mode (ICM) algorithm. Benchmark problems are strained from available energy functions used for stereo, image stitching, interactive segmentation, and denoising. Also a general-purpose software interface that allows vision researchers to effortlessly switch between optimization methods [05].

Ping Zhong, Runsheng Wang, 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 strong dependencies across spatial and spectral neighbors, which have been proved to be very useful for hyper-spectral image classification. Main task is to capture spatial dependencies in labels and observed image simultaneously and incorporating the classifications of hyper-spectral images with different statistics characteristics in a principled manner. Over-smoothing and over fitting are the important methods used to classify the hyper-spectral images using conditional random fields [06].

Yuliya Tarabalka, Mathieu Fauvel, Jocelyn Chanussot, Jón Atli Benediktsson, 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 refer the high number of spectral bands acquired by hyper-spectral sensors increases the potential to differentiate corporeal materials and objects, presenting new challenges to image analysis and classification. This improves classification accuracies when compared to other classification approaches. Investigate results are accessible for three hyper-spectral airborne images and compared with those obtained by advanced spectral-spatial classification techniques [07].

Ping Zhong, Runsheng Wang et all in their paper entitled "Modeling and Classifying Hyper-spectral Imagery by CRFs With Sparse Higher Order Potentials" focused the role of Sparse higher order potentials which reveal strong dependencies across spatial and spectral neighbors, which have been proved to be very helpful for hyper-spectral image classification. Here, overcomes this restraint by initial hyper-spectral image classification algorithm based on a CRF with sparse higher order potentials, which are particularly designed to integrate complex characteristics of hyper-spectral images. Capably implement the CRF model at training step, develops an capable local method under the piecewise training framework, while at supposition step, this proposes a simple strategy to unite the piece-wisely trained model to overcome the possible over-counting problems [08].

Guangyun Zhang,Xiuping Jia et all in their paper entitled "Simplified Conditional Random Fields With Class Boundary Constraint for Spectral-Spatial Base-Remote Sensing Image Classification" focused the role of Class boundary constraint using Conditional random fields (CRF) have been introduced to remote sensing image classification recently to combine contextual information into remote sensing classification. The advantages of the developed method are established in the experimental results using real remotely sensed data [09].

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 labeling methods in the discrimination of land-cover classes which evaluate that all methods already over smooth when most efficient, pointing out that there is a need to include more and more intricate prior information into the classification process. The ease supposition becomes more important as sensor resolutions keep escalating, both because the radiometric variability within classes increases and because remote sensing is employed in more heterogeneous areas, where shadow and shading effects, a mass of materials, etc., mortify the measurement data, and prior knowledge plays a greater role [10].

Yanfei Zhong, Xuemei Lin,Liangpei Zhang 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 the role of Mahalanobis distance boundary constraint is planned to perform the undertaking of classification for high spatial resolution (HSR) remote sensing imagery. To conserve the spatial details in the classification result, a Mahalanobis distance boundary constraint is measured as the spatial term to commence appropriate spatial smoothing [11].

Ji Zhao, Yanfei Zhong,Liangpei Zhang 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 Detail preserving smoothing classifier based on conditional random fields (DPSCRF) for HSR imagery is planned to apply the object-oriented strategy in the CRF classification framework, thus integrating the merits of both approaches to believe the spatial contextual information and conserve the detail information in the classification. In addition, the local class label cost also considers the changed label information of neighboring pixels at each iterative step in the classification to defend the detail information. In order to deal with the spectral variability of HSR imagery, segmentation prior is used by the object-oriented processing strategy [12].

III. THE SPATIAL LOCATION CUES

Spatial location cues are directly related to higher-order potentials. In remote sensing image classification, the spatial location shows the scenarios of "same material with different spectra" and "similar spectra from different materials". The higher-order potentials mainly model the spatial location to consider the nonlocal range of interactions between the target pixel and its nearest training samples for all the classes. The spatial location cues can make full use of the conformity of the image to model the nonlocal similarity of the land-cover type by the location information.

IV. The Spectral and Spatial Location Cues

The spectral cues are related to the unary potentials by the class membership probabilities. The spectral cues provide basic information of various land-cover classes, due to the difference in their spectra. The spatial location cues can provide more useful information for the classes that are easily confused with other land-cover types, which can also be used to calculate the class membership probabilities from another point of view. The spectral and spatial location cues can provide different information about the land-cover type from the spectral and spatial location, which helps to reduce the misclassification caused by the spectral similarity in remote sensing images.

V. The Spatial Contextual Information

The spatial contextual information is also used to overcome classification noise and obtain a relevant classification. The spatial contextual information is related to pair-wise potentials to consider the spatial interactions of neighboring pixels. Spatial information plays a fundamental role in the analysis and understanding of remotely sensed data sets. The significant improvement in accuracy in these applications confirms the importance of spatial information and the effectiveness of the relationship models.

VI. Conclusion

In this paper, a through literature survey has been studied by collecting and analyzing around 12-13 papers on image processing. Several techniques SVM, MLRMLL, SVRFMC etc have been studied. Accordingly, plan of implementation process is finalized to integrate spectral, spatial contextual and spatial location cues of high resolution images using conditional random fields (CRFSS).

So, after analyzing some techniques the expected result should be like as shown in graph.

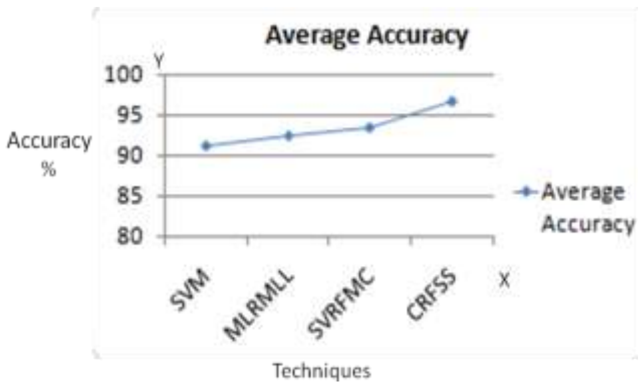

Fig.1.Average Accuracy among various Techniques

In graph, on the 'x axis' different techniques are there and on the 'y-axis' percentage accuracy are placed. CRFSS technique has highest average accuracy than other given techniques.

Integration of spectral location, spatial location cues and spatial contextual information I would like to do in my experiment which is using CRFSS algorithm.

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