A SURVEY OF HIGH RESOLUTION IMAGE CLASSIFICATION METHODS AND TECHNIQUES

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ABSTRACT

Classification is turning into a growingly valuable technique for giving huge zone of complete land cover data that utilize the images which has high resolution. High resolution images have the attributes of copious geometric and complete data and that data are useful to exhaustive classification. The proposed algorithm integrates three cues in CRF model by demonstrating the probabilistic potentials are spectral, spatial contextual and spatial location. The unary potentials displayed the spectral cues can gives essential data for separating the different land cover classes. The spatial contextual data modeled by the pair wise potentials that setting up the adjacent connections between pixels to support spatial smoothing. The higher order potentials unequivocally encode the spatial location cues. The non local scope of the spatial location associations into the objective pixel and its closest preparing tests is considered by the higher order potentials. This information can gives valuable data to the classes that are effectively mistaken for other land-cover types in the spectral appearance. We have proposed an image super resolution that employs image processing techniques to reproduce the image which has high resolution from a set of low resolution observations of the same scene.

Keyword: *-High Resolution, Image Classification, Remote Sensing, Spatial Contextual information, Spatial Location.*

1. INTRODUCTION

CLASSIFICATION means the procedure which is called as semantic segmentation in PC vision. Semantic segmentation is the procedure to allocate a predefined semantic mark to every pixel of an image. Image classification is the way toward allocating land cover classes to every pixel. Classification using high-resolution remote detecting symbolism has peaked up a great deal of consideration during the last couple of years, so the outcome is that the expanding accessibility of these remote detecting images. For exact earth perception from the distinctive sensor platforms (for example ROSIS, IKONOS and Quick Bird) these high resolution images can give enormous accessible information. The land-cover marking data of high resolution remote detecting symbolism got by classification assumes a critical part in different application areas, for example farming management, safety requisition, urban arranging and harm evaluation for ecological failure. To assign every pixel a label the prior classification techniques constantly utilized pixel level processing strategies. These techniques are additionally called pixelwise classification strategies. The pixelwise classification methods have been utilized as a part of numerous applications yet they don’t examine the abudant spatial relevant data of the images, so in high resolution image classification these techniques dependably result in a salt-and-pepper classification aspect. With a specific end goal to enhance the execution of classification, numerous scientists have tried to build complete utilization of the spatial data, and there have been loads of investigations of spectral-spatial classification.

2. LITERATURE SURVEY

To assign every pixel a mark, the prior classification methods constantly utilized a pixel-level handling methodology which are likewise called pixelwise classification methods, that freely think about the spectral data of every pixel by the utilization of a statistical learning algorithm, for example support vector machine (SVM) [1]. Dimension reduction or manifold learning strategies [2] can be utilized as a preprocessing step to acquire more illustrative features in the pixelwise classification. Probabilistic demonstrating based techniques [3], [4] have been effectively utilized for spectral-spatial classification. The probability map in the first place acquired by pixelwise classification for the probabilistic demonstrating based techniques, and it speeks to the probability of every pixel having a place with every land cover class. To consider the spatial data then by utilizing local filtering or an extended random walker strategy, the probability map is polished. Object-oriented classification method is one of the undeniable approaches that examine the spatial data to authorize smoothness. To accomplish the objectives of spectral-spatial classification the object-oriented classification [5] begins join the classification and segmentation algorithms. The segmentation is to start with led to part an image into homogeneous items. After that a majority voting strategy [6] is used to acquire the land-cover marks in light of pixelwise classification or direct classification in which item is taking as the fundamental unit. The segmentation can be accomplished by wide range of techniques for example, the fractal net evolution approach (FNEA) and the mean shift segmentation approach (MSS) [7] and it is the key advance in object-oriented classification. The object-oriented classification approaches intrinsically give the spatial data by picking item as the essential handling unit to lighten the salt-and-pepper classification noise. Still, The demanding activity in object oriented classification is the choice of the optimal segmentation scale because of the scale decent variety of the different land-cover types [8]. In an image analysis, the Markov random fields (MRF) model was firstly brought in 1984 [9]. The MRF model has been effectively utilized as a part of classification of numerous remote sensing image issues lately. For instance, for classification of remote sensing image the MLRMLL method has been effectively used which is nothing but multinomial logistic regression with active learning using a multilevel logistic spatial prior .By using multinomial logistic regression model the MLRMLL first takes in the class posterior probability. Then by enhancing the objective function of Markov Random Field with a multilevel logistic spatial prior classification can be acquired. The conditional random fields (CRF) are the progressed model of MRF that specifically models the posterior distribution, which is the thing that we need to evaluate in the classification task. CRF model can join the spatial contextual information in both labels and observed information and in this way the CRF model is more adaptable. CRF was first presented by Lafferty et al. [10] in 2001 for comprehending the labeling of 1D text sequences. In the next years, CRF has been generally used for remote sensing image classification and processing [11].

3. SYSTEM FLOW

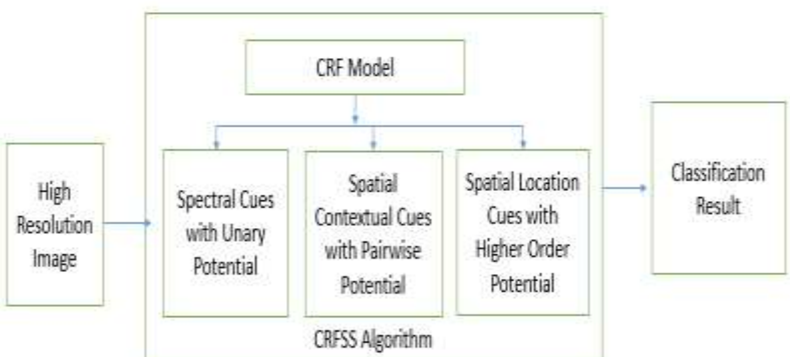

Fig -1: System Flow

The system flow is as shown in fig 1. The spectral, spatial contextual and spatial location cues (CRFSS) are integrating in conditional random field classification algorithm. The unary potential detailed the spectral cues with the help of class membership probabilities and this unary potential demonstrate the cost of single pixel picking a specific land cover mark. In light of the appearance highlight in the observed image by utilizing a discriminative classifier handle the class membership probabilities. Due to the diverse spectra the spectral cues give the essential data for segregating the different land cover types. On the observed image data the CRF model demonstrate the posterior probability of the labeled land cover map. The sharp and sudden disturbance in the image signal causes the Salt and Pepper noise. To defeat this noise the spatial contextual data is used. With the help of inference algorithms this acquires an attractive classification. The pair wise potential endeavor to acquire the preliminary information of spatial example like spatial smoothing. Spatial smoothing term is utilized to quantify contrast in appearance between the adjacent pixels. To consider the spatial contextual data, demonstrated by pair wise potentials that think about the spatial communications of adjacent pixels, the CRFSS algorithm acquires the benefits of the CRF model. Pairwise CRF can be planned as an extraordinary with the insertion of the unary potential in the pairwise potential. The spatial location cues are straightforwardly demonstrated by the higher order potential. To lighten the impact of spectral variability the spatial location cues are utilized in neighborhood locale. The higher order potentials unequivocally display the spatial area to consider the nonlocal scope of communications into the objective pixel and it's closest preparing tests for every one of the classes, in light of the spectral similarity of the similar type of land cover in a nearby region. Based on the class membership probabilities, in the CRFSS algorithm the spectral and spatial location cues can be combined and work together. The spatial location cues give additional valuable data to the classes that are effortlessly mistaken for other land-cover composes, which is encoded by the higher-order potentials. Likewise from another perspective which can be also used to compute the class membership probabilities. The spatial location and spectral cues can gives integral data related to the land-cover type, which eases the improper classification affected by the spectral similarity in remote detecting images. So in the CRFSS classification algorithm they are coordinated by the potential functions which based on the class membership probabilities. In CRFSS for demonstrating the potential functions, inference is used to advance the target work that is objective function and get the last label. With solid nearby least property an effective approximate inference algorithm has execute effectively in different uses of PC perception.

4. DATA SETS

Followings are the data sets for high resolution images.

4.1 Fancun QuickBird Dataset

This is the image from the fancun area in Hainan province, China which acquired in January 2010 by the QuickBird sensor. The image has a spatial dimension of 400 by 400 pixels and four spectral bands. It includes seven land cover classes: water, tree, grass, bare, building, road, and shadow.

4.2 Wuhan IKONOS Dataset

This is Wuhan IKONOS urban area remote sensing image with a 4-m spatial resolution that was recorded by the IKONOS sensor. This image is from Wuhan in Hubei province, China. It contains 400*600 pixels and four spectral channels. It also contains seven thematic classes.

4.3 Pavia Center ROSIS Dataset

This is an urban image acquired by the Reflective Optics System Imaging Spectrometer (ROSIS) optical sensor. It is from the center of Pavia, Italy. It consist of 1096*715 pixels, 102 spectral bands and spatial resolution of 1.3 m. This Pavia Center ROSIS dataset includes nine land cover classes: water, tree, grass, meadows, bricks, bare soil, asphalt, bitumen, tiles and shadow.

5. CONCLUSIONS

There are various image classification methods has been widely used. The conditional random field classification algorithm that integrating spectral cues, spatial contextual and spatial location cues is used for classification of high resolution images. Image Super resolution technique used for reconstructing the high resolution image from low resolution image, which aimed at conserving more conceivable useful details.

6. REFERENCES

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