RECONSTRUCTED HIGH RESOLUTION IMAGE CLASSIFICATION USING CRF

Ms. Archana N. Dhage[1], Dr. Varsha H. Patil[2]

[1] *ME Student, Department of Computer Engineering, MCOERC, Nashik, Maharashtra, India*
[2] *HOD, Department of Computer Engineering, MCOERC, Nashik, Maharashtra, India*

ABSTRACT

High resolution images have the characteristics of considerable geometric and element information, that are useful to special classification. With the rise within in availability of high resolution images, classification is changing into an increasing number of beneficial approaches for imparting a huge region of specific land cover statistics by using these high resolution images. With the full use of these attribute of high resolution images, the proposed algorithm integrates spectral, spatial contextual and spatial location cues in CRF model by demonstrating the probabilistic potentials. The unary potentials displayed the spectral cues can gives essential data for separating the different land cover classes. The spatial contextual data formed by the pairwise potentials that putting in the adjacent connections between pixels to support spatial smoothing. The higher order potentials without ambiguity encode the spatial location cues. The nonlocal 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 and which is immediately replicated in accuracy of classification. The experimental result shows the effectiveness of the algorithm compared with other image classification algorithm.

Keyword: - *High resolution image classification, conditional random fields, image super resolution, spatial contextual, spatial location.*

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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 discovering symbolism got by classification assumes an essential part in numerous application areas, for example farming management, safety requisition, urban arranging and harm evaluation for ecological failure. The prior techniques of classification continuously utilized a pixel-level processing method to employ mark for every pixel which are likewise known as pixelwise classification methods. The pixelwise classification methods have been utilized as a part of numerous applications yet they don't examine the abundant spatial relevant data of the images, so in high resolution image classification these techniques reliably end 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. For spectral spatial classification the probabilistic modeling based methods [3], [4] have been effectively utilized. The probability map in the first place acquired by pixelwise classification for the probabilistic demonstrating based techniques, and it speaks 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 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. 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]. So in late years, in remote sensing image classification the random field techniques have been generally used and that can think about the spatial association of pixels which is further valuable classification approach.

2. LITERATURE REVIEW

The prior techniques of classification continuously utilized a pixel-level dealing with method to employ mark for every pixel which are likewise known as 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 speaks 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 techniques intrinsically offer the spatial data by way of choosing item as the crucial 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 ARCHITECTURE

Figure 1 shows the block diagram of proposed system in which low or high resolution images are given as input to the system. If the image has high resolution then it is directly send to CRFSS algorithm for classification. If the image has low resolution then first reproduces an image having high resolution. For that here we have to use SRCNN which gives the high resolution image and after that the CRFSS algorithm is used for further processing with the use of neural network.

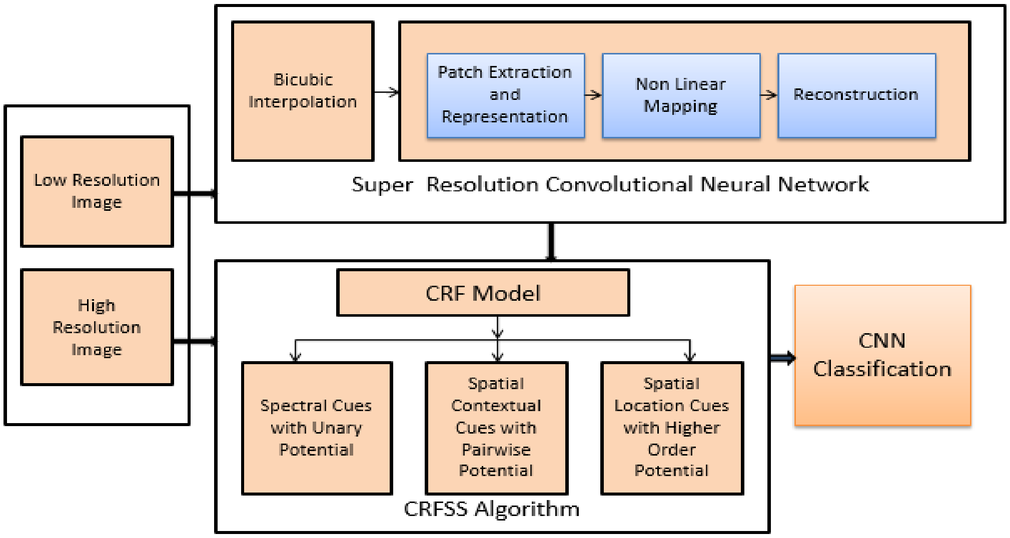

Fig -1: Block Diagram of Proposed System

3.1 CRFSS

In CRFSS 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 gives 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 pairwise 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, determine by pairwise potentials that think about the spatial communications of adjacent pixels, the CRFSS 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 without ambiguity encode the spatial location cues. The nonlocal scope of the spatial location associations into the objective pixel and its closest preparing tests is considered by the higher order potentials, in light of the spectral similarity of the similar type of land cover in a nearby region. Based on the class membership possibilities, within the CRFSS algorithm the spectral and spatial location cues is combined and work along. The spatial location cues gives additional valuable data to the classes that are effortlessly mistaken for other land-cover composes, which is encoded by the higher-order potentials and likewise from another perspective which can be also used to compute the class membership probabilities. The spectral and spatial location cues can gives integral data related to the land-cover type, which eases the improper classification caused by the spectral similarity in remote detecting images. So in the CRFSS classification algorithm they are coordinated by the potential functions 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 close least property an effective approximate inference algorithm has execute effectively in numerous uses of PC perception.

3.2 SRCNN

In SRCNN by using bicubic interpolation, first low-resolution image sharp up to the coveted size, which is just pre-processing. Consider this interpolated image as Y. Mapping function F(Y) consist of three operations: Extraction of patches and its representation, Nonlinear mapping and Reconstruction. The computation of these three operations based on filters W, biases B and convolution operation *.

Patch Extraction: In the patch extraction the coating patches are extracted from the low resolution image.

$$F1(Y) = \max (0, W1 * Y + B1)$$

After that every patch is represented as a high-dimensional vector. These high dimensional vectors involve a set of highlight maps, and which is the number equivalent to the dimensionality of the vectors. Here filter depends on its spatial size and quantity of channels of the input image.

Non Linear Mapping: In nonlinear mapping task every high dimensional vector nonlinearly maps onto another high dimensional vector.

$$F2(Y) = \max (0, W2 * F1(Y) + B2)$$

Every mapped vector is adroitly the portrayal of another patch which have high-resolution. Here these vectors involve other arrangement of feature maps and now these patches will be utilized for recreation.

Reconstruction: It totals the above high-resolution patch wise representations and which is finally used to create the last high-resolution image.

$$F(Y) = W3 * F2(Y) + B3$$

Likewise these three operations combine to form convolution neural network and used for obtain the final high resolution image. After that by using CRFSS algorithm high resolution imagery classification is proposed.

4. SYSTEM ANALYSIS

4.1 Working of CNN Algorithm

CNNs make the most spatially neighborhood correlation by way of implementing a nearby connectivity sample between neurons of adjacent layers.

The network has three layers:

1. Input layer: This takes the image as the input.
2. Output layer: Get the trained output from this layer.
3. Intermediate layers: Referred to as the hidden layers.

The network encompasses a series of convolution and sub-sampling layers.

Convolution Layer: This is the first layer of CNN network. Figure 2 shows its structure. With the help of convolution mask, bias term and a function expression it provides output. 5*5 convolution mask execute over 32*32 input feature map and gives output as 28*28. After adding bias, sigmoid function is applied on matrix.

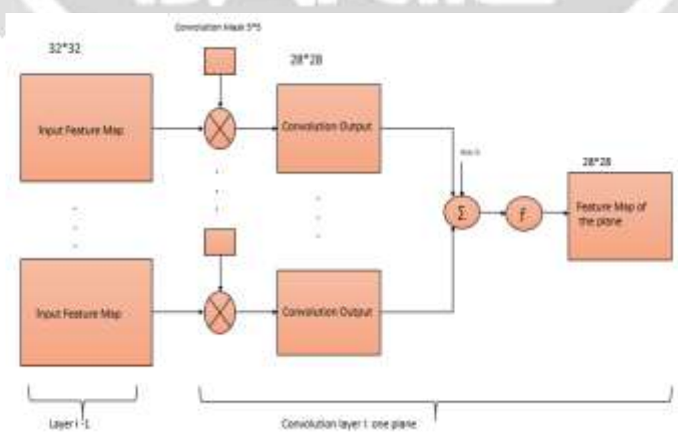

Fig -2: Working of Convolution Layer

Sub Sampling Layer: After convolution layer, in sub sampling layer use same number of plane as convolution layer. This layer provide reduced size feature map. For that in this layer divides the image into 2*2 and perform averaging. This layer does not conserve the information about exact relation rather than it conserves related data among features.

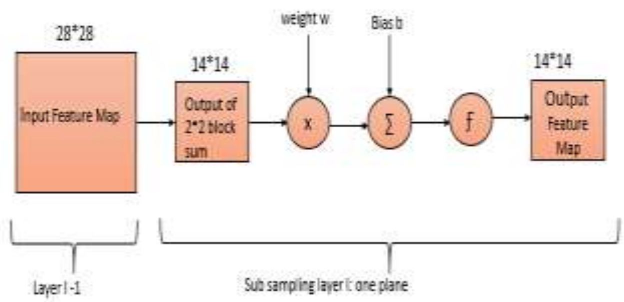

Fig -3: Working of Sub Sampling Layer

4.2 CRFSS Algorithm

1. Input: High-resolution image y = {y1, y2,…,yn} Where yi is the spectral vector of pixel i Ɛ V = {1,2,… , N} and N is the total number of pixels in the image.
2. A labelled land-cover map is represented as x = {x1, x2, . . . , xN}, with xi taking its value from the label set L = {1, 2, . . . , K}, where K denotes the number of classes.
3. Compute posterior probability of the label x conditioned on the observed image data y [12]:

$$P(x/y) = \frac{1}{Z}\exp\{-\sum_{c\in C}\varphi_{c(x_c,y)}\}$$

Where z: Partition function

C: Set of all cliques

$\varphi_{c(x_c,y)}$: Potential function, locally define in clique c

4. Then Define corresponding energy.

E $(x/y) = -logP(x/y) - \log z$ =

$$\sum_{c\in C}\varphi_{c(x_c,y)}$$

5. Then Compute Unary CRF model which is in the form of corresponding energy.
6. Compute pairwise CRF model with the sum of unary and pairwise potentials. With the help of spatial smoothing prior the pairwise potential is used to model spatial contextual cues.
7. Higher order CRF model can be then add the higher order potential defined over the cliques to capture the richer spatial interaction.
8. Then use α expansion inference to obtain satisfactory classification.
9. Get the classification of high resolution image.
10. Stop

5. RESULT

All modules in reconstruction and classification of high resolution image are implemented. Figure 4 shows reconstruction of one of the image with 870*870 pixels using image super resolution convolution neural network i.e. SRCNN.

Fig -4: Image before and after reconstruction

With the help of this implementation Graph 1 shows the comparison between bicubic, SRCN and our proposed CNN approach. PSNR (Peak Signal to Noise Ratio) is used as parameter for quality measurement between original and compressed image.

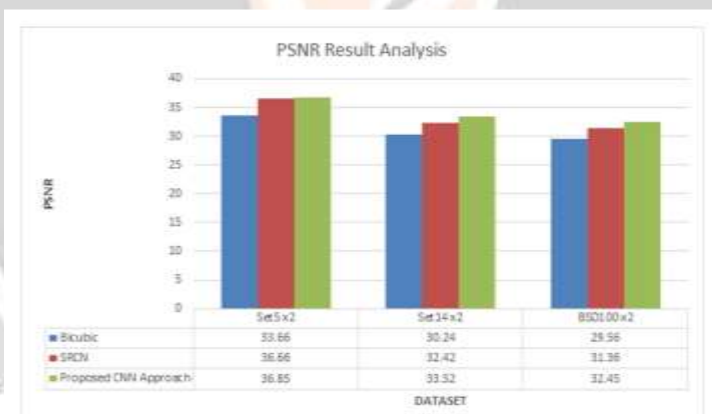

Chart -2: Image before and after reconstruction

After that comparison between an average accuracy of classification of this reconstructed image is as shown in Table 1.

Table -1: Comparison between two classification methods

Methods	Average Accuracy (%)
CRFSS Classifier	92.79
CNN Classifier	99.46

6. CONCLUSION

In the proposed system, the Super Resolution Convolution Neural Network takes in conclusion to end mapping amongst low and high resolution images with minimal additional pre or post preparing past the optimization and convert the low resolution image into the image which have high resolution. Then with the use of convolution neural network, conditional random field classification algorithm that integrating spectral cues, spatial contextual and spatial location cues is used for classification of high resolution image. So, together they provide good classification performance. This work motivates for several researches. However, assist enhancement went for safeguarding more possibly helpful subtle elements will be considered later on. Likewise, additionally the utilization of spatial location cues in methods like semi supervised learning classification will also be taking into consideration.

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