Missing Data Preprocessing and Reconstruction Techniques of Remote Sensing Images

Anju Aravind[1], Shabin P[2]

[1]M.Tech Student, Dept. of Electronics and Communication, College of Engineering Thalassery, Kerala, India
[2]Assistant Professor, Dept. of Electronics and Communication, College of Engineering Thalassery, Kerala, India

---

Abstract - *Remote sensing is the science of obtaining information about objects or areas from a distance, typically from aircraft or satellites.. Even it is an up growing field the remote sensing images suffer from data loss due to the bad atmospheric conditions such as haze, cloud as well as poor working conditions of the satellite.. The images with loss of data cannot be used for Further applications. This study includes a spatial–spectral adaptive haze removal and cloud removal methods. It is obvious to predict the missing data in existing remote sensing images. By using Tensor Singular Value Decomposition based Tensor Completion (TC) this problem can be overcome. There are number of methods for reconstructing missing data in remote sensing images .One of them is novel multi label RSIR approach supported fully convolutional network. Next is Tensor-Deep Stacking Network Spatial Temporal-Spectral (TDSN-STS) which helps to reconstructs the missing image in remote sensing statistics. Finally, Remote sensing deep neural network algorithms using an automatically search strategy is differently finds the acceptable spec for HRS image recognition tasks.*

Key Words: CNN, Remote sensing, Cloud removal, Haze removal, Tensor, TDSN-STS etc…

1. INTRODUCTION

Remote sensing image processing has been receiving more and more attention in this era due to the rapid developments of satellite technology. Quality of the remote sensing images are depends on the presence of clouds, excess haze, improper conditions of the satellite equipments etc. These clouds and hazes are contaminates at the surface of the earth so the satellites can't record the informations accurately. Presently various methods are available for removing clouds and haze from the observed remote sensing images. Cascaded convolutional neural networks, provides the better methods for the removal of these obstacles and reconstructions. Haze removal methods are spatially and spectrally based on adaptive strategies. As the demand of remote sensing image processing increasing the prediction, estimation and reconstruction of obtained images from the satellites are also increases. Remote sensing images are obtained within number of bands. Remote sensing images with missing information produces a lot of hitches. For overcoming these problems a Tensor-Deep Stacking Networking algorithms are used. Which works in all dimensions. Which helps to predict and reconstruct the missing image. Remote sensing images with missed data cannot be used for any other applications .If we can predict the chances or occurance of data loss it will be helpful during the processing techniques. An algebraic object which relates sets of objects with singular value decomposition is used here to predict and reconstruct the missed information. FCN based multi label RSIR approach is the first one .Especially, the fully convolutional network FCN is first programmed to soothsay segmentation

There are different methods for reconstructing the missing data of remote sensing images. A convolutional neural network map of each image in the considered image archive. As a result we will get multi label vector. After that extract region convolutional features of each images. By utilizing these extracted region feature region-predicated multi label vectors image retrieval is performed. Next method involves the combination of spatial ,temporal and spectral inputs which also based on a deep convolutional neural network (CNN). Here a unified deep CNN combined with spatial–temporal–spectral supplementary information. Actually most data retrieval methods are works with a single inputs. Which may be in spatial or temporal or in spectral domain. This combined method can solve multiple missing information reconstruction tasks. Finally the third method proposed here is the remote sensing deep neural network architecture. It is based on automatically search strategy and includes gradient search strategy.

2. PREPROCESSING OF REMOTE SENSING IMAGES

2.1. Haze Removal Method

Haze has several characteristics. It spreads over the large area of the earth according to the atmospheric conditions. The amount of haze spread is different from one band to the another. .To overcome this problem adaptive haze removal method is used. In spatial adaptive processing an atmospheric light estimation algorithm is used. The scattering intensity varied according to the spatial transformation. That's why used the light estimation algorithm.

The Adaptive spectral haze removal method rely on Atmospheric scattering law. Which states that "haze effects vary in different bands". Which indicates the transmission of light is heavily depends upon the wavelength of the light. A light wave with higher wavelength can transmit longer the distance. Similarly the light wave with lesser the wavelength can transmit the short distance. Whatever it may be transmission of light within the spectral bands are disregarded. Actually this is the main reason of incomplete removal of presence of haze different spectral bands. So gradient based approach is employed to remove haze in all visible bands.

2.2. Cloud Removal Methods

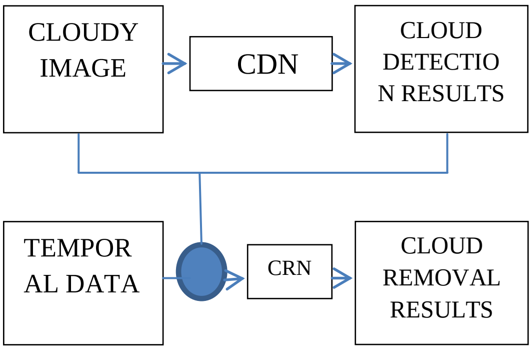

Fig -1: Integrated Cloud Removal architecture

The figure.1 shows the proposed framework for cloud detection and cloud removal tasks. As shown here we can see two convolutional neural networks. Which are fully convolutional neural networks(FCN).The first network is for the detection of clouds which are added up in the current input remote sensing image. It is abbreviated as CDN. The second network is employed for removing the clouds which are detected in the first stage. It is abbreviated as CRN. The input image with clouds is goes to the first convolutional network which detects the clouds in the image. The results from the CDN network and the temporal image corresponding to the input data are added up and goes to the second convolutional neural networks. From this stage the detected clouds are removed. The CDN and CRN network algorithms are designed in such a way to detect and remove the clouds in the remote sensing images.

2.2. Prediction of Missing data

In satellite image processing Tensors with deep stacking neural networks is used to predict the missing information in the obtained remote sensing images. The figure.2 below shows the three module network structure for the training and prediction of loss information. It consist of three modules as shown below. Three modules are actually the three training stages. That is modules are the indication of training stages. If there is five modules then it will goes through five training stages.

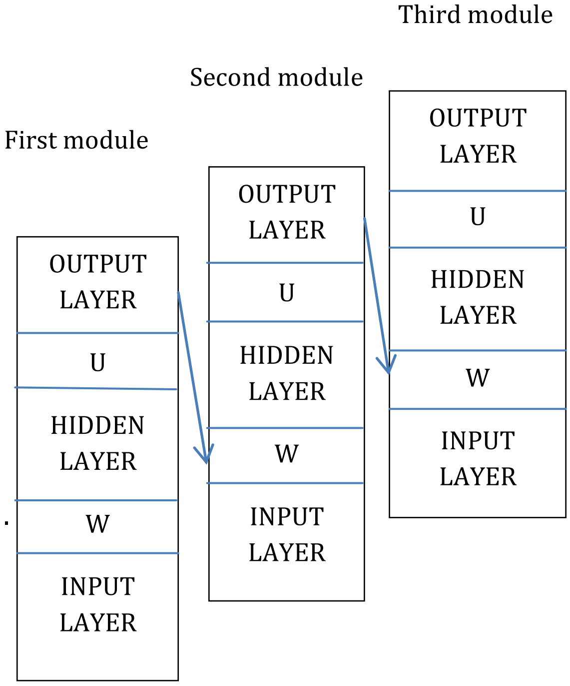

Fig -2: Architecture of TDSN

Each module contains five blocks. The first block is the input layer and last block is the output layer. There is a hidden layer occurred between the weighting vectors u and w. weight vector u maps between output layer and hidden layer and weight vector w maps between hidden layer and input layer. The input to the bottom input layer is the raw input image. The output from each layer is pass to the input of the next module. Output layer will learn about the spatial and spectral features of the resultant image. The final output layer gives the actual predicted image which is in the vector form.

3. DIFFERENT MISSING DATA RECONSTRUCTION TECHNIQUES AND ALGORITHMS

3.1 Tensor single value decomposition method based low rank tensor completion.

A remote sensing images consist of different bands. Distortion or loss occur among these bands. Sometimes some bands are free from the data loss and these bands contains the full information. The presently used tensors only utilizes one or two bands for the image reconstruction. This is the one of the reason for the incomplete retrieval of the loss information. To overcome these problems a Tensor Singular value decomposition based tensor completion is employed. It uses both spectral information and spatial information in all bands of the remote sensing images. An article which discuss the image reconstruction presented by H.Shen et al.[2] shows the image reconstruction by this method.

3.2 Multi label approach based on fully convolutional neural network

The traditional image reconstruction techniques works with single label. It may contain the more vital part of the obtained image .But we should bother about the multiple classes of the images. Because an image lies in multiple classes. So the single label image reconstruction techniques leads to quality loss of the reconstructed image. Thats why the multi label approach based on fully convolutional neural network is introduced. It is discussed in detail by the Z. shao et al.[6].Multi label approach make use of large no of data sets. Usually the conventional methods includes different steps for doing these retrieval tasks. They are image segmentation, feature extraction and image annotation. But in multi label approach based on fully convolutional neural networks these three steps are combined in a single frame.

3.2 Combined spatial temporal spectral convolutional neural network algorithms

As mentioned earlier most of the missing data reconstruction techniques which uses single input. That is it will perform a single reconstruction work. It performs the reconstruction tasks with input in any one of the domain(spectral or spatial or temporal). Information from the other domain neglected. Considering these limitations or problems an effective reconstruction task which utilizes multilple input source is introduced. That is the combined spatial temporal spectral convolutional neural network architecture. It can itself remove cloud, haze as well as reconstruct the missing information.

The architecture contains five segments. During the mixing up of multi source data two inputs are given. One in the spectral domain other may be in temporal or spatial domain. These inputs are changes accordingly. Convolutional feature extraction unit is the heart of this setup. From there it undergoes multiple convolution operations. It is followed by dilated convolution which is differ from the normal convolution operations in such a way that it can perform same filters at different range. Then boosting the perfomance of the multiple inputs a boosting up task is also included in the network. The final block of this architecture is skip connection. This is employed to overcome the limitations of the deep convolutional neural network as it may affected by gradient vanishing problem. Description of each block is presented by Q.zhang et el [10].

3.4 Tensor deep stacking networks with spatial temporal spectral input data

For the reconstruction missing data with tensor deep stacking networks numerous data sets and training stages are employed. Each stage corresponds to each module as in [4].Accuracy and efficiency is increased than the any other existing works. Actually it is a supervised learning model. The missing data is during each module and is compared with the actual image. This predicted and actual images are compared to check the accuracy. There will be a threshold value and if the compared result is below this threshold value the process is continued as explained in [4].

3.5 Remote sensing deep neural network

It achieves efficient performance without the help of manual modeling and works based on gradient descent. The main contributions of these techiniques are remote sensing deep neural network search frame, gradient based search architecture search and a task driven architecture search as in [8]. It works on the two stage cascade optimization technology and automatically finds the appropriate convolutional neural networks for the image recognition tasks. Which are explained in detail in [8].These are the main missing data reconstruction techniques associated with convolutional neural networks. Algorithms are performed in appropriate platforms according to the need.

4. CONCLUSIONS

In this article, discussed about remote sensing technology and its limitations during the image processing tasks. As we know remote sensing growing as the demand of satellite image processing is increases. Excess haze, thick cloud and other bad atmospheric conditions are the main reasons for the distortion of the remote sensing images. By using deep convolution algorithms we can solve these problems. Spatial and spectral adaptive haze removal techniques are for the detection and removal of the haze., and is efficient for use with single remote sensing images with different scenes and various types of haze. In the cloud removal technique employed two FCNs that formed the main body of the framework, and similarly an efficient cloud detection and removal methods are also employed with the help of convolutional neural networks. Presently used missing data reconstruction methods are also discussed in this article which are all make use of deep convolutional networks or its variants.

REFERENCES

[1] M. Shao, C. Wang, T. Wu, D. Meng and J. Luo, "Context-Based Multiscale Unified Network for Missing Data Reconstruction in Remote Sensing Images," in IEEE Geoscience and Remote Sensing Letters, doi: 10.1109/LGRS.2020.3021116M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[2] M. Srindhuna and M. Baburaj, "Estimation of Missing Data in Remote Sensing Images Using t-SVD based tensor completion," 2020 International Conference for Emerging Technology (INCET), Belgaum, India, 2020, pp. 1-5, doi: 10.1109/INCET49848.2020.9153980.

[3] S. Ji, P. Dai, M. Lu and Y. Zhang, "Simultaneous Cloud Detection and Removal From Bitemporal Remote Sensing Images Using Cascade Convolutional Neural Networks," in IEEE Transactions on Geoscience and Remote Sensing, doi: 10.1109/TGRS.2020.2994349.

[4] D. Palanisamy and R. Senthilkumar, "Predicting Missing Image in Remote Sensing Time Series Using Spatial-Temporal-Spectral Data," 2019 Third International Conference on Inventive Systems and Control (ICISC), Coimbatore, India, 2019, pp. 146-150, doi: 10.1109/ICISC44355.2019.9036376.

[5] G. Yuan and Q. Hao, "Digital watermarking secure scheme for remote sensing image protection," in China Communications, vol. 17, no. 4, pp. 88-98, April 2020, doi: 10.23919/JCC.2020.04.009.

[6] Z. Shao, W. Zhou, X. Deng, M. Zhang and Q. Cheng, "Multilabel Remote Sensing Image Retrieval Based on Fully Convolutional Network," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 318-328, 2020, doi: 10.1109/JSTARS.2019.2961634

[7] H. Shen, C. Zhang, H. Li, Q. Yuan and L. Zhang, "A Spatial–Spectral Adaptive Haze Removal Method for Visible Remote Sensing Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 58, no. 9, pp. 6168-6180, Sept. 2020, doi: 10.1109/TGRS.2020.2974807.

[8] J. Wang, Y. Zhong, Z. Zheng, A. Ma and L. Zhang, "RSNet: The Search for Remote Sensing Deep Neural Networks in Recognition Tasks," in IEEE Transactions on Geoscience and Remote Sensing, doi: 10.1109/TGRS.2020.3001401.

[9] L. Khelifi and M. Mignotte, "Deep Learning for Change Detection in Remote Sensing Images: Comprehensive Review and Meta-Analysis," in IEEE Access, vol. 8, pp. 126385- 126400, 2020, doi: 10.1109/ACCESS.2020.3008036.

[10] Q. Zhang, Q. Yuan, C. Zeng, X. Li and Y. Wei, "Missing Data Reconstruction in Remote Sensing Image With a Unified Spatial–Temporal–Spectral Deep Convolutional Neural Network," in IEEE Transactions on Geoscience and Remote Sensing, vol. 56, no. 8, pp. 4274- 4288, Aug. 2018, doi: 10.1109/TGRS.2018.2810208.

[11] W. He, H. Zhang, L. Zhang, and H. Shen, "Total-variation-regularized low-rank matrix factorization for hyperspectral image restoration,"IEEE Transactions On Geoscience And Remote sensing, vol. 54, pp. 178-188, January 2016.