Remote Sensing Image Fusion Using Sparse Representation and Deep CNN

Naluguru Udaya Kumar, Ayan Das Gupta, Syed Basha Shaik, Anooja B, Bhasker Pant and Jayaram Ramesh

April 27, 2022

Remote Sensing Image Fusion using Sparse Representation and Deep CNN

Naluguru Udaya Kumar
Associate Professor,
Department of Electronics and Communication Engineering,
Marri Laxman Reddy Institute of Technology and Management,
Hyderabad,Telangana, India
unaluguru@gmail.com

Ayan Das Gupta
WBES, Assistant Professor,
Postgraduate Department of Geography,
Chandernagore Government College,
Hugli, West Bengal, India
dasguptaayan11111@gmail.com

Syed Basha Shaik
Assistant Professor,
Department of Computer Science and Engineering,
K L University,
Vijayawada, India
syedshaik2010@kluniversity.in

Anooja B
Assistant Professor,
Department of Electronics and Communication Engineering,
Malabar College of Engineering and Technology,
Thrissur, Kerala, India
anooja@malabarcet.ac.in

Bhasker Pant
Professor,
Department of Computer Science and Engineering,
Graphic Era Deemed to be University,
Dehradun, Uttarakhand, India
pantbhaskar2@gmail.com

Jayaram Ramesh
Assistant Professor,
Department of Mechanical Engineering,
Lourdes Matha College of Science and Technology,
Kuttichal, Kerala, India
jayaramvijayan@gmail.com

Abstract-Remote sensing image fusion seems such as be an effective approach to make utilization of a big quantities of data through multiple sensors. Many remote sensing applications require both high spatial as well as high spectral resolutions, especially for GIS-based applications, but instead different earth satellites such as SPOT, Landsat 7, as well as IKONOS provide both panchromatic (Pan) images at a higher spatial resolution as well as multispectral (MS) images at a lower spatial resolution, and many remote sensing applications require both high spatial as well as high spectral resolutions. A remote sensing image fusion methodology is developed that seems to be utilize a deep convolutional neural network to absorb spectral and spatial features from source images. To generate a fused MS image having high spatial resolution, remote sensing image fusion can combine the spatial detail of a panchromatic (PAN) image with the spectrum information of a low-resolution multispectral (MS) image.

Keywords-panchromatic (Pan) images, multispectral (MS) images.

I INTRODUCTION

Remote sensing's resolution images is always constrained in optical remote sensing due to onboard storage and bandwidth. As a result, panchromatic (PAN) multispectral (MS) photos as well as images with high spatial resolution with high spectral resolution are frequently provided by remote sensing satellites. The conception of sparse representation indicates that a common image can always be adequately described through only a few coefficients as well as descriptions.Deepan, P., and L. R. Sudha et al.[8] previously suggested a Convolutional Neural Network accuracy for object categorization relying on average feature fusion. Cai et al.[7] has evaluated the fusion of Light Detection and Ranging (LiDAR), Hyperspectral Images (HS), as well as extremely high-resolution Visible (Vis) images using a multi-sensor classification technique based on deep learning ensemble procedure and decision fusion framework.

Shen, Huanfeng, [9] has suggested a PAN/MS fusion technique that includes the a significant residual gradient CNN in a model-based approach.Chen, Yuehong et al. [10] have introduced a new spatiotemporal image fusion method for remote sensing approach for 2 pairs of CR–FR images focused on two multiscale convolutional neural networks (STFMCNN).Wang et al. [11] has introduced to forecast Landsat-like photos, researchers employed a residual convolution neural network, which may be used even if only two past images are available.

The portions of this paper is organised as follows. Section I describes introduces remote sensing image fusion. The related works are described in Section II. The proposed design is shown in Section III. In Section IV, the experimental results and discussions are presented. The conclusion are summarised in Section V.

II RELATED WORKS

Hu and Qiu has described based on sparse representation and guided filtering, an unique multi-modality image fusion approach. [12]. Raza and Asif [13] have developed IR-MSDNet as an innovative as well as effective deep architecture for learning robust and discriminative salient representations in order to execute IR and visible image fusion. Nirmalraj et al. [14] employing the deep learning technique, propose compressive sensing for effective visible and infrared image fusion sparse representation convolutional F-CSR.

In urban places, Bigdeli et al. [15] has provided a collection of deep learning methods for hyperspectral expansion, LiDAR, and visible RGB data. From RGB and LiDAR data, first, certain textural and height data were retrieved. A fusion strategy for multimodal medical images has been established [16], which is based on the SGF and SR. Vaish et al. [17] has created Multi-Resolution Singular Value Decomposition is used to reduce fused images using a sparse representation (MSVD).

Wu, Yuanyuan, et al. [18] have developed RDFNet, data fusion over three channels using a distributed fusion framework based on residual CNN (RCNN). A novel change detection method combining SR as well as a capsule network has been proposed by Wang et al.[19]. Tan et al. [20] have proposed a weighted GSR model-based picture fusion approach. Shibu et al. [21] has developed a new multiscale decomposition-based CNN as well as SR-based diagnostic medical fusion approach.

III PROPOSED METHODOLOGY

Employ a remote sensing image fusion approach based on sparse representation as well as deep CNN to enhance the quality of certain fused image.First, apply sparse coefficients to shows the actual images in the approach. Second, the high values of panchromatic (Pan) image sparse coefficients are reduced to 0. Third, the linear weighted averaging fusion approach is being utilised to implement the coefficients of panchromatic (PAN) as well as multispectral (MS) images.

Finally, the united sparse coefficients as well as deep CNN are combined to rebuild the fused image.The spatial resolution of PAN images is often considerable, while the spectral resolution is modest, although the immense spectral resolution, MS images have a low spatial resolution and the high spectral resolution.

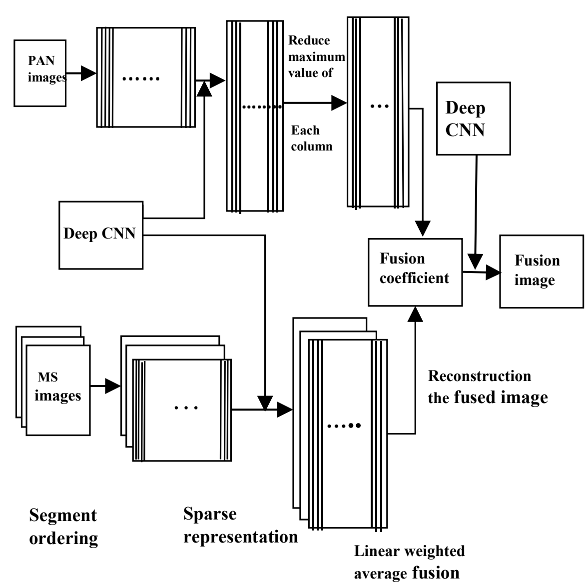

Fig 1: schematic diagram of proposed remote sensing image fusion

Only few coefficients could be employed to characterize a signal in sparse representation theory. The image's leading feature is frequently characterized by the maximum of sparse coefficients. The maximums in a remote sensing image incorporate spectral data, meanwhile the minimums represent spatial data.

3.1 Remote Sensing Image Fusion Based on Deep CNN

When using multi resolution analysis or sparse representation to accomplish image fusion, for example, the first step is to use a dictionary of base filters or atoms to express the source images. The second stage entails determining the most acceptable techniques, such as weights differences are produced once the expressions have been derived. Image Fusion's objective is to develop a high-resolution MS image. As an outcome, the network generates a high spatial resolution label MS image from both a PAN as well as a low spatial resolution MS image as input data.

A convolution operation is defined as:

$$F = ReLU(X_0 w) \quad (1)$$

In (1), $ReLU$ indicates the activation function, X_0 is the convolution inputand w represents the convolution kernal.

3.2 Sparse Representation

Sparse representation involves the use redundant data to represent information in a more general and effective manner, particularly corresponds towards how individuals interpret data. The SR's intention is to identify the fewest nonzero atoms among all possible solutions by finding the sparsest coefficients. As a result, the overcomplete dictionary and sparse coding are two of the most significant aspects of SR. On the one hand, patches are used to split a number of training images.

IV RESULTS AND DISUSSION

On various pairs of multi focus images, the suggested method is compared to the standard fusion algorithms of Brovey transform (Brovey), intensity-hue-saturation (IHS), principal component analysis (PCA), discrete wavelet transform (DWT), as well as fast discrete curvelet transform (FDCT).

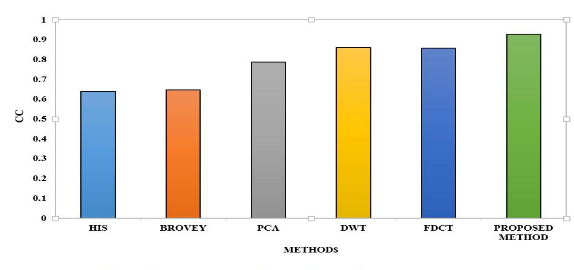

Fig 2: Various methodologies in statistical evaluation histograms of Correlation Coefficient (CC) findings in IKONOS Data

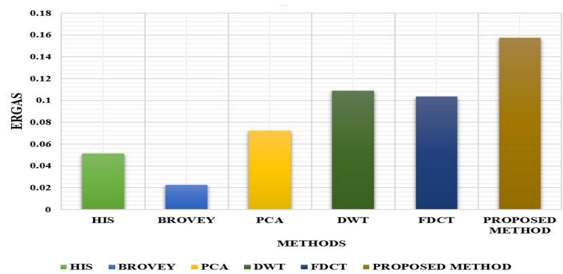

Fig 3: ERGAS outcomes histograms analysed statistically using several ways (IKONOS Data).

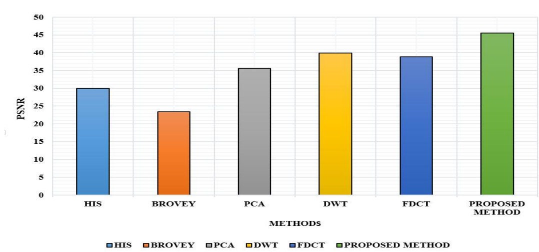

Fig4:PSNR observations statistical evaluation histograms employing several approaches (IKONOS Data).

The correlation coefficient (CC), ERGAS, as well as PSNR canutilized to assess the fusion images' high spectral resolution information. According to Figures (2), (3), and (4), the propose method's CC is higher, whereas ERGAS and PSNR are lower.

V CONCLUSION

This work presents a significant contribution by offering a sparse representation and deep convolution neural network-based remote sensing image fusion framework. The proposed method is capable of processing various bands of MS images as well as various sorts of PAN objects. It has a high fusion quality: the proposed methodology can dependably combine the MS image spectral information and also the Pan Image spatial information.

References

1. Zhu, Hao, Mengru Ma, Wenping Ma, Licheng Jiao, Shikuan Hong, JianchaoShen, and Biao Hou. "A spatial-channel progressive fusion ResNet for remote sensing classification." *Information Fusion* 70 (2021): 72-87.
2. Sun, Yan, C. H. Zhao, and J. Li. "Remote sensing image fusion algorithm based on NSCT and PCA transform domain." *Journal of Shenyang University of Technology* 33, no. 3 (2011): 308-314.
3. Kumar, J. Thrisul, G. VENU RATNA Kumari, M. Satish Kumar, K. Pradeep Vinaik, and P. Raju. "A Fusion of SA Rand Optical Remote Sensing Images for Urban Object Extraction Using Multiple Discrete

Wavelet Families." *Annals of the Romanian Society for Cell Biology* 25, no. 4 (2021): 2399-2407.

4. Lu, Han, DanyuQiao, Yongxin Li, Shuang Wu, and Lei Deng. "Fusion of China ZY-1 02D Hyperspectral Data and Multispectral Data: Which Methods Should Be Used?" *Remote Sensing* 13, no. 12 (2021): 2354.
5. Sulaiman, Asmaa G., Walaa H. Elashmawi, and Gh S. Eltaweel. "IHS-based pan-sharpening technique for visual quality improvement using KPCA and enhanced SML in the NSCT domain." *International Journal of Remote Sensing* 42, no. 2 (2021): 537-566.
6. Kaur, Harpreet, DeepikaKoundal, and VirenderKadyan. "Image fusion techniques: a survey." *Archives of Computational Methods in Engineering* 28, no. 7 (2021): 4425-4447.
7. Cai, Weiwei, Zhanguo Wei, Runmin Liu, Yuan Zhuang, Yan Wang, and XinNing. "Remote sensing image recognition based on multi-attention residual fusion networks." *ASP Transactions on Pattern Recognition and Intelligent Systems* 1, no. 1 (2021): 1-8.
8. Deepan, P., and L. R. Sudha. "Fusion of deep learning models for improving classification accuracy of remote sensing images." *J Mech Continua Math Sci* (2019): 189-20.
9. Shen, Huanfeng, Menghui Jiang, Jie Li, Qiangqiang Yuan, Yanchong Wei, and Liangpei Zhang. "Spatial–spectral fusion by combining deep learning and variational model." *IEEE Transactions on Geoscience and Remote Sensing* 57, no. 8 (2019): 6169-6181.
10. Chen, Yuehong, Kaixin Shi, Yong Ge, and Ya’nan Zhou. "Spatiotemporal remote sensing image fusion using multiscale two-stream convolutional neural networks." *IEEE Transactions on Geoscience and Remote Sensing* 60 (2021): 1-12.
11. Wang, Xiaofei, and Xiaoyi Wang. "Spatiotemporal fusion of remote sensing image based on deep learning." *Journal of Sensors* 2020 (2020).
12. Hu, Qiu, Shaohai Hu, and Fengzhen Zhang. "Multi-modality image fusion combining sparse

representation with guidance filtering." *Soft Computing* 25, no. 6 (2021): 4393-4407.

13. Raza, Asif, Jingdong Liu, Yifan Liu, Jian Liu, Zeng Li, Xi Chen, Hong Huo, and Tao Fang. "IR-MSDNet: Infrared and Visible Image Fusion Based On Infrared Features and Multiscale Dense Network." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14 (2021): 3426-3437.
14. Nirmalraj, S., and G. Nagarajan. "Fusion of visible and infrared image via compressive sensing using convolutional sparse representation." *ICT Express* 7, no. 3 (2021): 350-354.
15. Bigdeli, Behnaz, Parham Pahlavani, and HamedAminiAmirkolaee. "An ensemble deep learning method as data fusion system for remote sensing multisensor classification." *Applied Soft Computing* 110 (2021): 107563.
16. Li, Qiaoqiao, Weilan Wang, Guoyue Chen, and Dongdong Zhao. "Medical image fusion using segment graph filter and sparse representation." *Computers in Biology and Medicine* 131 (2021): 104239.
17. Vaish, Ankita, and Saumya Patel. "A sparse representation based compression of fused images using WDR coding." *Journal of King Saud University-Computer and Information Sciences* (2022).
18. Wu, Yuanyuan, Mengxing Huang, Yuchun Li, Siling Feng, and Di Wu. "A distributed fusion framework of multispectral and panchromatic images based on residual network." *Remote Sensing* 13, no. 13 (2021): 2556.
19. Wang, Shaona, Yanan Wang, Yang Liu, and Linlin Li. "SAR image change detection based on sparse representation and a capsule network." *Remote Sensing Letters* 12, no. 9 (2021): 890-899.
20. Tan, Jin, Taiping Zhang, Linchang Zhao, XiaoliuLuo, and Yuan Yan Tang. "Multi-focus image fusion with geometrical sparse representation." *Signal Processing: Image Communication* 92 (2021): 116130.
21. Shibu, D. Sunderlin, and S. SujaPriyadharsini. "Multi scale decomposition based medical image

fusion using convolutional neural network and sparse representation." *Biomedical Signal Processing and Control* 69 (2021): 102789.