BLUR KERNEL'S EFFECT ON PERFORMANCE OF SINGLE-FRAME SUPER-RESOLUTION ALGORITHMS FOR SPATIALLY ENHANCING HYPERION AND PRISMA DATA

Kavach Mishra¹*, Rahul Dev Garg¹

¹ Geomatics Engineering Group, Civil Engineering Department, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand, India 247667 - (kmishra, rdgarg) @ce.iitr.ac.in

KEY WORDS: Hyperspectral remote sensing, single-frame super-resolution, image quality, Wald's protocol

ABSTRACT:

Single-frame super-resolution (SFSR) achieves the goal of generating a high-resolution image from a single low-resolution input in a three-step process, namely, noise removal, up-sampling and deblurring. Scale factor and blur kernel are essential parameters of the up-sampling and deblurring steps. Few studies document the impact of these parameters on the performance of SFSR algorithms for improving the spatial resolution of real-world remotely-sensed datasets. Here, the effect of changing blur kernel has been studied on the behaviour of two classic SFSR algorithms: iterative back projection (IBP) and gaussian process regression (GPR), which are applied to two spaceborne hyperspectral datasets for scale factors 2, 3 and 4. Eight full-reference image quality metrics and algorithm processing time are deployed for this purpose. A literature-based re-interpretation of Wald's reduced resolution protocol has also been used in this work for choosing the reference image. Intensive intra-algorithm comparisons of various simulation scenarios reveal each algorithm's best performing Gaussian blur kernel parameters. Inter-algorithm comparison shows the better performing algorithm out of the two, thereby paving the way for further research in SFSR of remotely-sensed images.

1. INTRODUCTION

1.1 Background

High resolution (HR) images possess high pixel density, thereby offering detailed information. Their requirement is usual in computer vision tasks to improve image analysis and pattern recognition performance. Remote sensing exercises like large scale mapping need high spatial and spectral resolution, implying the need for HR. Hyperspectral images (HSI) (Goetz et al., 1985) have a large number of contiguous bands which provide much information about features but at the cost of low spatial resolution. On the other hand, multispectral images (MSI) offer a high spatial resolution. These images acquired by conventional cameras offer little spectral content. Because of innate sensor constraints and optics manufacturing technology, a compromise between comprehensive spatial and spectral content cannot be reached. Resolution improvement techniques can solve this predicament. These are fusion (Pohl and Van Genderen, 1998), interpolation (Meijering, 2002), super-resolution (SR) (De Santis and Gori, 1975) and restoration (Andrews and Hunt, 1977).

A lower spatial resolution image is combined with a high spatial resolution image in the fusion process to obtain an output with high spatial resolution. However, the spectral properties may be lost, or the resultant output may have pronounced blurring (Kwan et al., 2017). In interpolation, the low resolution (LR) image is transformed into the HR space, and a function is utilized to find the missing figures. But, interpolation operators omit the high-frequency information of the LR input image (Gotoh and Okutomi, 2004). The size of the output and input images remains the same in the case of restoration. SR prevails over these limitations by retaining the spectral properties as well as

SR is an inverse imaging problem, which reverses the degradation process initiated by the imaging model to generate the HR image from its LR image (Nasrollahi and Moeslund, 2014), i.e.,

$$I_{HR} = B^{-1} [\Delta^{-1} (I_{LR} - \eta)]$$
(1)

Where, $I_{HR} = HR$ output B = Blurring operator Δ = Down sampling operator $I_{LR} = LR$ input η = Additive noise

B is sensor dependent and provided in the technical specification document as the point spread function (PSF) (Fernandez-Beltran et al., 2017). Although theoretically represented by a Bessel function (Chen et al., 2018), B can be appropriately represented by a Gaussian function to account for the lens aberration and atmospheric turbulence during image acquisition (Fernandez-Beltran et al., 2017). Scale factor (SF) governs Δ .

Depending on the number of input LR images, SR can be multiframe or single-frame. Figure 1 shows a functional classification of spatial domain SR algorithms depending on the image type (Nasrollahi and Moeslund, 2014; Fernandez-Beltran et al., 2017; Jiang, J. et al., 2020)

enhancing the spatial features of the LR dataset(s) at a larger spatial scale (Protter et al., 2008)

^{*} Corresponding author



Figure 1. Functional Classification of Spatial Domain SR

1.2 Choice of SR Algorithms for HSI SR and Their Evaluation

It is not possible to acquire multiple images of the same scene in many exercises or it is costly and time-consuming. There exist many case studies of extending grayscale/red green blue (RGB) multi-frame SR for real-world HSI SR. However, these algorithms succeed only in spatial enhancement and the outputs may suffer from co-registration issues or partial preservation of spectral information.

Multi-frame or single-frame methods designed specifically for HSI SR require spectral response functions for end member estimations or large amount of training data which may lack labelling. Moreover, they have a high computation cost owing to requirement of parallel processing routines. Their implementation is shown only on a few benchmark datasaets such as CAVE (Yasuma et al., 2010), Salinas (Plaza et al., 2005), and Pavia (Dell'Acqua et al., 2003).

Dearth of open source real-world HR references makes the validation of the generated super-resolved outputs challenging (Ghamisi et al., 2017). Only spectral angle mapper (SAM) (Yuhas et al., 1992) is used to assess spectral quality during quality metric evaluations. No detailed spectral profile examinations have been done in existing literature to support the claim that grayscale/RGB single-frame SR algorithms do not consider the spectral content of the original HSI data during the SR output generation.

Also, there exist applications where application of grayscale/RGB single-frame SR algorithms is economically feasible (Fernandez-Beltran et al., 2017). Therefore, there is a need to revisit use of single-frame SR in HSI and study effect of blur kernel on SR algorithm's performance, which is largely absent in many case studies.

1.3 Objectives

The objectives of the present study are to

- apply classic (grayscale/RGB) single-frame SR algorithms to real world HSI data
- assess the performance of these algorithms under changing blur kernel parameters for different SF

1.4 Study Area

The area of investigation occupies an area of 38.8 square kilometres (sq. km.) in Ahmedabad, Gujarat, India. Figure 2 shows its location. It is characterized by the densely settled walled city, lands of closed textile mills, well-planned commercial, residential and educational areas. The Sabarmati river is the major natural feature in the scene.



Figure 2. Study Area Location

2. MATERIALS AND METHODS

2.1 Data Used

Tables 1 and 2 present the sensor and scene specifications of the HSI data used in this study, respectively.

Sensor Name	Hyperion	PRecursore IperSpettrale della Missione
		Applicativa (PRISMA)
Spectral Bands	242 (70 bands in Visible and Near Infra-Red (VNIR) and 172 in Short Wavelength Infra- Red (SWIR))	239 (66 bands in VNIR and 173 in SWIR)
Spatial Resolution	30 m	30 m
Wavelength Range	400 - 1000 nm (VNIR) 900 - 2500 nm (SWIR)	400 – 1010 nm (VNIR) 920 – 2505 nm (SWIR)
Swath Width	7.5 km	30 km
Spectral	10 nm	\leq 12 nm
Resolution Radiometric Resolution	12 bit	12 bit
Temporal Resolution	16 days	29 days

Table 1. HSI Sensor Specifications (Pearlman et al., 2001;Italian Space Agency, 2020)

Sensor Name	Hyperion	PRISMA
Product Type	L1T	L2D
Entity ID	EO1H1490442002 308110PZ_1T	PRS_L2D_STD _202010050601 03_2020100506 0107_0001

Date of	04.11.2002	05.10.2020
Acquisition		
Scene Centre	22°55'04.24"N	22° 58' 49.8"N
Latitude		
Scene Centre	72°31'44.09"E	72°33'57.24"E
Longitude		
Radiometric	12 bit	12 bit
Resolution		
Temporal	16 days	29 days
Resolution	10 4495	_>
Cloud Cover	0%	0.3438%
Coordinate	UTM Zone 43 N	Unknown WGS
Projection System	WGS 84	84
with Datum		

Table 2. Scene Specifications

2.2 Methodology

2.2.1 HSI Data Pre-processing: For Hyperion, a square subset of 209 samples and 209 lines bounding the study area is extracted. Following this, zero, noisy and water absorption bands are removed leaving 128 bands in the dataset. Along track destriping is also done for the removal of bad columns, which arise due to calibration differences in temporal variation and response of Hyperion detector arrays (Han et al., 2002). Atmospheric correction by the Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH; Adler- Golden et al., 1999) provides accurate, physics-based derivation of apparent surface reflectance (Kruse et al., 2004). The surface reflectance values are scaled band-wise to the range of 0 to 1 through division by 10000.

The VNIR-SWIR stacked PRISMA data in Environment for Visualizing Images (ENVI) standard format is extracted using the R programming language package "prismaread" (Busetto

and Ranghetti, 2020) along with scene metadata in separate files. It is co-registered with Hyperion using 1° affine transformation and spatial subsetted into a square patch of identical samples and lines. Bands with haziness, single and multiple columns of no data or very low radiometric accuracy, and pixels possessing a very low radiometric accuracy are removed and only 112 bands are remaining in the dataset.

2.2.2 SR Algorithm Execution: The chosen classic SR algorithms: Iterative Back Projection (IBP) (Elad and Feuer, 1996; Yang et al., 2014) and Gaussian Process Regression (GPR) (He and Siu, 2011) show outstanding performance in literature in terms of quick processing speed, visual appeal of the generated HR imagery and efficient extraction of spatial and spectral properties from the input data (Yang et al., 2014; Fernandez-Beltran et al., 2017; Mishra et al., 2019). The SR algorithms are executed band-wise on a single machine with configuration: Random Access Memory (RAM) = 16 GB, Processing Speed= 2.5 GHz, Central Processing Unit (CPU)= Intel Core i5-10300H to examine its calculation productivity.

Single-frame IBP focusses on the iterative refinement of an initial guess of super-resolved image, i.e., reconstruction error between LR image and LR version of super-resolved image is minimized throughout the iterative process. The iterations continue until the maximum number of iterations or a limit in the reconstruction error is reached. The parameters are: Backprojection Kernel Window = Gaussian, size dependent on standard deviation (sigma) = 0.1 - 2.1, iterations = 100, SF = 2, 3 and 4

GPR is a hybrid framework consisting of two stages. In the first stage, the input LR image is bicubically interpolated to the target

spatial resolution. Each pixel in the super-resolved output is predicted by that pixel's neighbours in the interpolated output. The structural information defining the pixel's neighbourhood is used for this purpose. In the second stage, the output obtained in the first stage is deblurred. The final super-resolved output with sharper edges is produced by learning from a training set of LR and HR image pairs. This training set is obtained from the input LR image and the interpolated output. The parameters are: Patch size = 20×20 , Overlapping Factor = 0.66, PSF = Gaussian, size = SF and calculated according to sigma, sigma = 0.1 - 2.1, SF = 2, 3 and 4

It is also assumed that the original HR image of the scene area is not accessible, and hence determination of the optimal value for every parameter of each algorithm is not possible.

2.2.3 Performance assessment of SR algorithms: The super-resolved image's quality is assessed using 8 full-reference quality indices for every SF and changing blur kernel parameters. These metrics are: bias, cross-correlation (CC), difference in variance (DIV), error relative globale adimensionnelle de synthèse (ERGAS), entropy, root mean square error (RMSE), relative average spectral error (RASE), and universal image quality index (Q). Reader may refer to Vaiopoulos (2011) for more information on these indices.

In the absence of a suitable HR reference image, reducedresolution protocol (Wald et al., 1997) is used. According to this protocol, original HSI dataset is the ground truth for SR product, assuming that the LR version of the SR product has as much resemblance as possible to the original HSI data. Considering the ill-posed nature of the SR problem (Lugmayr et al., 2022), uniform imaging model parameters are taken: a blur kernel window size calculated according to $\sigma = 0.1 - 2.1$ and scale factor = 2, 3 and 4 for generating the LR version of every superresolved output (Loncan et al. 2015).

3. RESULTS AND DISCUSSION

3.1 IBP

Figures 3 to 10 show the effect of blur kernel size and standard deviation on IBP's performance using RASE, Q, RMSE, ERGAS, E, CC, DIV and bias.





RASE figures lie between 0.82 - 8.02. Irrespective of SF, Hyperion's RASE values are lower than PRISMA's RASE values. For SF=2, there is a steep rise in RASE values from $\sigma =$ 0.5, size = 6 x 6 to the highest RASE at $\sigma = 2.1$, size = 16 x 16 RASE values for x3 Hyperion and x4 PRISMA almost overlap each other until $\sigma = 1.3$. For each SF, lowest RASE exists for $\sigma =$ 0.1, size = 4 x 4 in case of SFs 2 and 4 and size = 3 x 3 in case of SF = 3.



Figure 4. Effect of Blur Kernel Width Using Q on IBP's Performance

Q values are above 0.9 for each scenario. For x2 Hyperion and x2 PRISMA, there is a sharp decline from $\sigma = 0.5$ onwards whereas for other SFs the decline is not so sharp. The lowest decline is in case of SF=4 with SF=3 being intermediate of the two. Again $\sigma = 0.1$ shows the highest Q for each SF irrespective of the dataset.



Figure 5. Effect of Blur Kernel Width Using RMSE on IBP's Performance

RMSE values are very low. For x2 Hyperion and x2 PRISMA, there is a steep rise as in the case of RASE from $\sigma = 0.5$ onwards. There is not much difference in the RMSE values for x3 Hyperion and x4 PRISMA as the blur kernel parameters change. Again $\sigma = 0.1$ shows the lowest RMSE for each SF irrespective of the dataset.



Figure 6. Effect of Blur Kernel Width Using ERGAS on IBP's Performance

Range of ERGAS values is almost half the range of RASE values irrespective of SF, kernel values and dataset. For x2 Hyperion and x2 PRISMA, there is a steep rise from $\sigma = 0.5$ onwards whereas for other SFs the rise is not so sharp. The lowest rise is in case of x4 Hyperion followed by x4 PRISMA and x3 Hyperion. Again $\sigma = 0.1$ shows the lowest ERGAS for each SF irrespective of the dataset.



Figure 7. Effect of Blur Kernel Width Using E on IBP's Performance

E values for both PRISMA and Hyperion show a similar pattern except the values being lower in case of Hyperion due to more number of bands (128) than the PRISMA data (112). Again $\sigma = 0.1$ shows the highest E for each SF irrespective of the dataset.



Figure 8. Effect of Blur Kernel Width Using CC on IBP's Performance

CC values are above 0.9 for each scenario. For x2 Hyperion and x2 PRISMA, there is a sharp decline from $\sigma = 0.5$ onwards whereas for other SFs the decline is not so sharp. The lowest decline is in case of SF=4 with SF=3 being intermediate of the two. Again $\sigma = 0.1$ shows the highest CC for each SF irrespective of the dataset



Figure 9. Effect of Blur Kernel Width Using DIV on IBP's Performance

DIV values are positive, increasing with rising kernel size and σ . The sharpest rise is in the case of x2 PRISMA from $\sigma = 0.5$ onwards. For x3 PRISMA the rise in values begins from $\sigma = 0.4$. x3 Hyperion and x4 PRISMA almost overlap each other with rising kernel size and σ . Again $\sigma = 0.1$ shows the lowest DIV for each SF irrespective of the dataset.



Figure 10. Effect of Blur Kernel Width Using Bias on IBP's Performance

Bias values are mostly negative, very small in absolute terms and tending towards 0 with rising kernel size and σ indicating similarity with the original data. Bias has a uniform value for x2 Hyperion and x2 PRISMA irrespective of the changing blur kernel parameters.

3.2 GPR

Figures 11 to 18 show the effect of blur kernel size and standard deviation on GPR's performance using RASE, Q, RMSE, ERGAS, E, CC, DIV and bias.



Figure 11. Effect of Blur Kernel Width Using RASE on GPR's Performance

RASE figures fall between 4.04 – 8.84. Irrespective of SF, Hyperion's RASE values are lower than PRISMA's RASE values. For SF=2, there is a steep rise in RASE values from σ = 0.8 size = 6 x 6 to the highest RASE at σ = 2.1 size = 16 x 16. For SF=3, RASE values rise from σ = 0.4, plateauing at σ = 1.5 and then declining slightly with increasing kernel parameters. For each SF, lowest RASE exists for σ = 0.1, size = 4 x 4 in case of SFs 2 and 4 and size = 3 x 3 in case of SF=3.



Figure 12. Effect of Blur Kernel Width Using Q on GPR's Performance

Q values are above 0.9 in each scenario. For x4 Hyperion and x4 PRISMA, the values decline from $\sigma = 0.5$ to $\sigma = 1.5$ and remain unchanged with rising kernel parameters. For SF = 2, the values peak at $\sigma = 0.6$ and decline with rising kernel parameters.



Figure 13. Effect of Blur Kernel Width Using RMSE on GPR's Performance

RMSE values are very low, though slightly higher than IBP. For x2 Hyperion and x2 PRISMA, there is a steep rise from $\sigma = 0.7$ onwards. Again $\sigma = 0.1$ shows the lowest RMSE for each SF irrespective of the dataset

Effect of Blur Kernal Width Using ERGAS



Figure 14. Effect of Blur Kernel Width Using ERGAS on GPR's Performance

Steepest rise in ERGAS is for x2 PRISMA from $\sigma = 0.6$. x3 and x4 Hyperion do not show much rise in values. The rise in x4 Hyperion begins from $\sigma = 0.7$, peaks at $\sigma = 1.5$ and reduces slightly, whereas in x3 Hyperion the rise happens from $\sigma = 0.7$ and the rise continues with increasing kernel size and σ . x3 PRISMA rises from $\sigma = 0.5$ to peak at $\sigma = 1.1$ and overlap with x2 Hyperion at $\sigma = 1.2$, then decrease till $\sigma = 1.5$ and rise slightly thereafter.



Figure 15. Effect of Blur Kernel Width Using E on GPR's Performance

E values for both PRISMA and Hyperion show a similar pattern except the values being lower in case of Hyperion due to more number of bands (128) than the PRISMA data (112). Again $\sigma = 0.1$ shows the highest E for each SF irrespective of the dataset Higher information preservation is visible in GPR compared to IBP.



Figure 16. Effect of Blur Kernel Width Using CC on GPR's Performance

CC values are above 0.9 in each scenario. For x4 Hyperion and x4 PRISMA, the values decline from $\sigma = 0.5$ to $\sigma = 1.5$ and remain unchanged with rising kernel parameters. For SF = 2, the values peak at $\sigma = 0.6$ and decline with rising kernel parameters.



Figure 17. Effect of Blur Kernel Width Using DIV on GPR's Performance

DIV values are positive, increasing with rising kernel size and σ . The sharpest rise is in the case of x2 PRISMA from $\sigma = 0.5$ onwards. For x3 PRISMA the rise in values begins from $\sigma = 0.4$ in a concave shape till $\sigma = 1.1$ and then rising slowly to match the DIV values of x2 Hyperion from $\sigma = 1.8$ onwards. x4 Hyperion and x4 PRISMA almost overlap each other with rising kernel size and σ . Again $\sigma = 0.1$ shows the lowest DIV for each SF irrespective of the dataset



Figure 18. Effect of Blur Kernel Width Using Bias on GPR's Performance

Bias has a uniform value for x2 Hyperion and x2 PRISMA irrespective of the changing blur kernel parameters. A parabolic curve for x3 PRISMA, x4 PRISMA and x4 Hyperion.

4. CONCLUSION

Since this is an ongoing work, conclusions can be drawn only after compilation of the processing times and and use of peak signal-to-noise ratio (PSNR), SAM and structural similarity index measure (SSIM) for investigating impact of changing blur kernel parameters on SR algorithm's performance.

ACKNOWLEDGEMENTS

We would like to thank the United States Geological Survey (USGS) and the Agenzia Spaziale Italiana (ASI) for providing the Hyperion and PRISMA datasets free of charge for scientific research.

REFERENCES

Adler-Golden, S. M., Matthew, M. W., Bernstein, L. S., Levine, R. Y., Berk, A., Richtsmeier, S. C., Acharya, P. K., Anderson, G. P., Felde, G., Gardner, J., Hike, M., Jeong, L. S., Pukall, B., Mello, J., Ratkowski, A., and Burke, H. -H. 1999. Atmospheric correction for shortwave spectral imagery based on MODTRAN4. *SPIE Proc. Imaging Spectrometry*, 3753:61-69

Andrews, H. C., & Hunt, B. R. 1977. *Digital image restoration*. New Jersey: Prentice-Hall

Busetto, L., & Ranghetti, L. 2020. " prismaread: A tool for facilitating access and analysis of PRISMA L1/L2 hyperspectral imagery." V. 1.0.0. https://github.com/lbusett/prismaread/ (November 30, 2020)

De Santis, P., & Gori, F. 1975. On an iterative method for superresolution. *Optica Acta: International Journal of Optics*, 22(8), 691-695.

Dell'Acqua, F., Gamba, P., & Ferrari, A. 2003. Exploiting spectral and spatial information for classifying hyperspectral data in urban areas. *International Geoscience and Remote Sensing Symposium (IGARSS), l,* 464–466. https://doi.org/10.1109/igarss.2003.1293810

Elad, M., & Feuer, A. 1996, November. Super-resolution reconstruction of an image. In *Electrical and Electronics Engineers in Israel, 1996, Nineteenth Convention of* (pp. 391-394). IEEE

Fernandez-Beltran, R., Latorre-Carmona, P., & Pla, F., 2017. Single-frame super-resolution in remote sensing: a practical overview. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431161.2016.1264027

Ghamisi, P., Yokoya, N., Li, J., Liao, W., Liu, S., Plaza, J., ... & Plaza, A. 2017. Advances in hyperspectral image and signal processing: A comprehensive overview of the state of the art. *IEEE Geoscience and Remote Sensing Magazine*, 5(4), 37-78.

Goetz, A. F., Vane, G., Solomon, J. E., & Rock, B. N. 1985. Imaging spectrometry for earth remote sensing. *science*, 228(4704), 1147-1153.

Gotoh, T., & Okutomi, M. 2004, June. Direct super-resolution and registration using raw CFA images. In *Proceedings of the* 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004. CVPR 2004. (Vol. 2, pp. II-II). IEEE.

Han, T., Goodenough, D. G., Dyk, A., & Love, J. 2002. Detection and Correction of Abnormal Pixels in Hyperion Images. In *International Geoscience and Remote Sensing Symposium* (pp. 1327–1330). Toronto: IEEE. https://doi.org/10.1109/IGARSS.2002.1026105

He, H., & Siu, W. C. 2011, June. Single image super-resolution using Gaussian process regression. In *CVPR 2011* (pp. 449-456). IEEE.

Italian Space Agency. 2020. PRISMA products specification document. Rome, Italy. http://prisma.asi.it/missionselect/docs.php (November 30, 2020)

Jiang, J., Sun, H., Liu, X. & Ma, J. 2020. Learning Spatial-Spectral Prior for Super-Resolution of Hyperspectral Imagery, in *IEEE Transactions on Computational Imaging*, vol. 6, pp. 1082-1096, doi: 10.1109/TCI.2020.2996075

Kruse, F. A. 2004, March. Comparison of ATREM, ACORN, and FLAASH atmospheric corrections using low-altitude AVIRIS data of Boulder, CO. In *Summaries of 13th JPL Airborne Geoscience Workshop, Jet Propulsion Lab, Pasadena, CA.*

Kwan, C., Choi, J. H., Chan, S., Zhou, J., & Budavari, B. 2017, March. Resolution enhancement for hyperspectral images: A super-resolution and fusion approach. In 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 6180-6184). IEEE.

Loncan, L., De Almeida, L. B., Bioucas-Dias, J. M., Briottet, X., Chanussot, J., Dobigeon, N., Fabre, S., Liao, W., Licciardi, G. A., Simoes, M., Tourneret, J. Y., Veganzones, M. A., Vivone, G., Wei, Q., & Yokoya, N. 2015. Hyperspectral Pansharpening: A Review. *IEEE Geoscience and Remote Sensing Magazine*, *3*(3), 27–46.

Lugmayr, A., Danelljan, M., Yu, F., Van Gool, L., & Timofte, R. 2022. Normalizing Flow as a Flexible Fidelity Objective for Photo-Realistic Super-resolution. *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, 1756–1765. https://doi.org/10.1109/wacv51458.2022.00095

Meijering, E. 2002. A chronology of interpolation: from ancient astronomy to modern signal and image processing. *Proceedings of the IEEE*, *90*(3), 319-342.

Mishra, K., Siddiqui, A., Kumar, V. & Garg, R. D. 2019. Enhancing Resolution of Hyperspectral Data: A Comparative Study in Urban Area. In ISG-ISRS National Symposium on Innovations in Geospatial Technology for Sustainable Development with special emphasis on NER, November 22 - 24, 2019 at North Eastern Space Applications Centre (NESAC), Shillong, India

Nasrollahi, K., & Moeslund, T.B., 2014. Super-resolution: A comprehensive survey. *Machine Vision and Applications*. https://doi.org/10.1007/s00138-014-0623-4

Pearlman, J., Segal, C., Clancy, P., Nelson, N., Jarecke, P., Ono, M., ... & Carman, S. 2001. The EO-1 Hyperion imaging spectrometer. In *IEEE Aerospace Conference*.

Plaza, A., Martínez, P., Plaza, J., & Pérez, R. 2005. Dimensionality reduction and classification of hyperspectral image data using sequences of extended morphological transformations. *IEEE Transactions on Geoscience and Remote Sensing*, 43(3), 466–479. https://doi.org/10.1109/TGRS.2004.841417

Pohl, C., & Van Genderen, J. L. 1998. Review article multisensor image fusion in remote sensing: concepts, methods and applications. *International journal of remote sensing*, *19*(5), 823-854. Protter, M., Elad, M., Takeda, H., & Milanfar, P. 2008. Generalizing the nonlocal-means to super-resolution reconstruction. *IEEE Transactions on image processing*, 18(1), 36-51.

Vaiopoulos, A. D. 2011. Developing Matlab scripts for image analysis and quality assessment. *Earth Resources and Environmental Remote Sensing/GIS Applications II Event: SPIE Remote Sensing, 12897806*(10). https://doi.org/10.1117/12.897806

Wald, L., Ranchin, T., & Mangolini, M. 1997. Fusion of satellite images of different spatial resolutions: Assessing the quality of resulting images. *Photogrammetric Engineering and Remote Sensing*, *63*(6), 691–699.

Yang, C.-H., Ma, C. and Yang, M.-H. 2014. Single-Image Super-Resolution: A Benchmark. In *European Conference on Computer Vision*, 8692: 372-386. Berlin, Heidelberg: Springer.

Yasuma, F., Mitsunaga, T., Iso, D., & Nayar, S. K. 2010. Generalized assorted pixel camera: postcapture control of resolution, dynamic range, and spectrum. *IEEE transactions on image processing*, 19(9), 2241-2253.

Yuhas, R., Goetz, A. F. H., & Boardman, J. W. 1992. Descrimination among semi-arid landscape endmembers using the Spectral Angle Mapper (SAM) algorithm. *Summaries of the Third Annual JPL Airborne Geoscience Workshop, JPL Publ.* 92–14, Vol. 1, 147–149.