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Hyper spectral Image Restoration using Low Rank Matrix Recovery and Neural Network

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Abstract*:*Hyper spectral images are those where each pixel forms an almost continuous spectrum. They have experienced significant success but in practice they are degraded by a mixture of various types of noises i.e. Gaussian noise, dead pixels or lines, stripes and so on. A Hyper Spectral Image restoration method is introduced which is based on low-rank matrix recovery (LRMR) and Neural Network which remove the Gaussian noise, dead pixels or lines and stripes. This algorithm is applied on different size of images having different spectral bands. In order to recover the missing pixels or neighbouring pixels, connected component analysis with indexing is used. This paper proposes image restoration of hyper spectral images using LRMR and Neural network which promise qualitative and quantitative result of the degraded images in terms of Peak Signal to Noise Ratio, Mean Square Error, Bit Error Rate and Structural Similarity Index.

***Keywords:* Hyper spectral images, Image restoration, LRMR, Neural network**

1.INTRODUCTION

Hyper spectral pictures square measure those wherever every element forms associate virtually continuous spectrum. They need intimate with vital success however in follow it suffers from numerous degradations like blurring thanks to incorrect focus, movement and different image defects (incorrect exposure and distortion), noise contamination, positioning error and missing information. As a result the visual look and also the applications of hyper spectral pictures square measure severely influenced. Applications like agriculture, forestry, mapping and then on. Thus HSI restoration is a full of life space. So, many alternative denoising strategies are projected for the restoration of HSIs.

1.1 Image Restoration is the process to manipulate a given image so that result obtained is more suitable than the original image. It sharpens or improves the image features such as edges, boundaries or contrast which are helpful for display and analysis.The greatest difficulty in image restoration is identifying the criterion for restoration. A large number of image restoration techniques require interactive procedures to obtain satisfactory results.

Image restoration done by two ways:

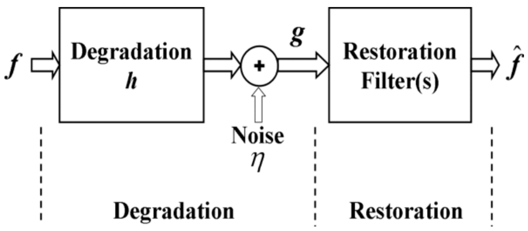

Figure 1: RestorationModel

- Spatial domain
- Frequency domain

2. TECHNIQUES USED

2.1 LOW RANK MATRIX RECOVERY

Digital image method plays an important role inside the investigation and rationalization of remotely perceived data. Image restorations techniques ease in enhancing the visibility of any 0.5 or feature of the image by dominant the information in several elements or properties. Image restoration improves the clarity of objects inside the scene by raising the brightness distinction between objects and their backgrounds. Image restorations unit unremarkably conducted as a distinction stretch followed by a tonal restoration.

Applications of the Low Rank Matrix Recovery is to square measure to unravel the problems of image process with a relevancy a replacement restoration technique set on real-coded particle. The main target of the projected LRMR is to extend and enlarge the distinction and detail in a picture by modifying the boundaries of a completely unique extension to an area restoration technique.
Matrix representations of complex systems and models emerging in various areas usually have the character that such a matrix is framed of a sparse matrix and a low-rank matrix. These types of applications include the model selection in

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statistics, system testimony in engineering, partially consistent decomposition in optical systems and matrix harshness in computer science.

Low-rank and distributed structures are very ready in matrix completion and compressed sensing. “Go Decomposition” (GoDec) is used to systemized and durably evaluate the low-rank part. GoDec can be enlarged to solve multi-label learning problem by dissolving the multi-label data into the aggregate of various low-rank part and a sparse unused, where each low-rank part approaches to the plotting of a specific label in the feature space. Then estimation can be acquired by finding the combined sparse representations of a new sample on the subspaces defined by the low-rank parts.

Features:

(i) Consider noisy low-rank and sparse decomposition which are the most important conditions of real data.

(ii) Now control the rank of the low-rank unit and the sparsity of the sparse unit that saves time and space costs by trade-off within efficiency and accuracy.

(iii) Randomized low-rank approximation method i.e. "Bilateral Random Projection (BRP)" is developed to further improve the update.

(iv) Linear convergence and wellness to the noise can be proved in a manner by the strategy of "alternating projections on manifolds".

(v) Systemized solution to other problems like matrix completion and multi-label learning.

2.2 NEURAL NETWORKS

Artificial neural networks are composed of interconnecting artificial neurons. The factitious neural networks are wont to acquire the data of biological neural networks and for resolution computing issues. Artificial neural network algorithms plan to abstract the complexness associated target what matter most from a science purpose of read.

Properties of NN are:

- Good performance i.e. better results.
- Good predictive ability: Genuine Acceptance Rate high: number of times better result.
- Low generalization error: False acceptance rate will be high.

The other incentive for this idea is to lower the mixture of estimation needed to imitate artificial neural networks to permit one to experiment with larger networks and to line them on larger information sets.

Identification and management, pattern recognition (face identification; object recognition); sequence identification (gesture, speech, written text recognition); medical diagnosis; money, etc. area unit the most application areas of ANN.

A.Architecture of Artificial Neural Network:There are three types of neural layers in the basic architecture of artificial neural network which are input; hidden and output.

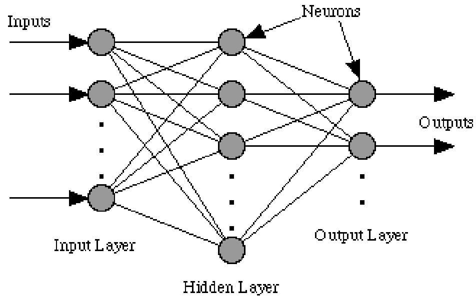

Figure 2: Architecture of NN

In feed-forward networks, the flow of signal is strictly during a feed-forward direction that's from input to output units. The information process will more expand over multiple layers of units; however there's no feedback connections exist. Feedback connections are gift in repeated networks. The contrary to feed-forward networks is that the impulsive properties of the network are necessary. for a few cases, activation values of the network properties of the network units bear a relaxation method in such some way that the network can amendment to a stable state within which these activations don't amendment.

B. Feed Forward Neural Networks:Feed-forward ANNs allow signals to flow in a technique solely i.e. from input to output. No feedback (loops) is there therefore the output of any layer doesn't influence that very same layer. The Feed-forward ANNs tend to be uncomplicated networks that link inputs with outputs. They’re principally utilized in pattern recognition. This sort of organisation is additionally called bottom-up or top-down. Single-layer perceptron’s, multilayer perceptron’s and radial basis perform square measure sorts of feed forward neural networks.

C. Single Layer Perceptron’s:The basic sort of neural network could be a single-layer perceptron’s network that contains one layer of output nodes and also the inputs area unit directly passed to the outputs through a series of weights. This can be thought-about because the simplest quite feed-forward network. Then total of the merchandise of the weights and also the inputs area unit computed in every node. If the worth is on top of threshold it takes ‘1’ otherwise it takes ‘-1’. Neurons with this sort of activation operate are referred to as artificial neurons or linear threshold units. The literature the term perceptron’s usually refers to networks consisting of 1 of those units and an analogous nerve cell was delineate by Warren McCulloch and music director Pitts within the Forties. If the edge worth lies between the 2 then a perceptron’s are often developed victimisation one and -1 state.

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Largely perceptron's have outputs of one or -1 with a threshold of zero and there's some proof that such networks are often lined quicker than networks generated from nodes with numerous activation and deactivation values. So Perceptron's are often lined by an easy formula that's the delta rule. This calculates the distinction between calculated output associate degree sample outputs and uses them to come up with an adjustment to the weights for implementing a style of gradient descent. Single-unit perceptron's area unit solely capable of learning linearly dissociable patterns.

D. Delta Rule: The delta rule is a gradient descent learning rule for updating the weights of the artificial neurons in a single-layer perceptron. This is a special case of the more general back propagation algorithm. For a neuron j with activation function g(x); the delta rule for j's; ith weight is given by:

$$\Delta W_{ij} = (t_j - y_j)\, g\, (h_j) x_i$$

Then delta rule is commonly stated in simplified form for a perceptron's with a linear activation function as

$$\Delta W_{ij} = \alpha\, (t_j - y_j)\, x_i$$

where α is known as the learning rate parameter.

E. Multi-Layer Neural Networks: This category of networks contains multiple layers of machine units that square measure interconnected during a feed-forward method and in every single layer; every vegetative cell has direct connections with the neurons of the following layer. Thus the units of those classes of networks apply a sigmoid operate as AN activation operate in numerous applications. Then universal approximation theorem for neural networks states that each continuous operate that maps intervals of real numbers to some output interval are often approximated arbitrarily closely by a multi-layer perceptron's with only one hidden layer. The result holds for restricted categories of activation functions for e.g.-the sigmoid functions. The Multi-layer networks use varied learning techniques and also the preferred being back-propagation. Then output values square measure compared with the right values to work out the worth of some predefined error-function. With the assistance of assorted techniques, the error is fed back via a network. The formula arranges the weights of every affiliation to attenuate the worth of the error operate by some quantity. By duplicating this method for a sufficiently additional variety of coaching cycles, the network can typically almost like some state wherever the error of the calculations square measure minimum. during this case, the network has learned an exact target operate and to regulate weights properly a general methodology for non-linear optimisation that's referred to as gradient descent is applied. The spinoff of the error operate in relevancy the network weights square measure computed and so weights square measure modified in such the way that the error get minimize. Thanks to this reason back-propagation will solely be used on networks with differentiable activation functions.

2.3CONNECTED COMPONENT ANALYSIS

When the region boundaries have been detected or perceived, the regions which are not separated by a boundary are often useful to extract. Any set of pixels which is not partitioned by a boundary is call connected. Each maximal sector of connected pixels is called a connected component. The partition an image into segments is done by the set of connected components.

CC = bwconncomp (BW) send back CC that is established in BW. BW can be of any size and CC is a four field's composition.

It has default property i.e. eight for 2 dimensions, twenty six for 3 dimensions and conndef(ndims(BW),'maximal') for larger dimensions.

CC = bwconncomp (BW,conn) describes the property for the connected elements. The sequent scalar values for channelize are:

(i) Connectivity's for 2 dimensions
4-connected neighbourhood
8-connected neighbourhood
(ii) Connectivity's for 3 dimensions
6-connected neighbourhood
18-connected neighbourhood
26-connected neighbourhood

3. RELATED WORK

H. Liu et al. proposed a 3-D tensor diffusion matrix based kernel regression HSI denoising method. Kernel regression has been shown to be a powerful image denoising technique. After analyzing the geometric feature of eigenvectorsof 3-D tensor matrix, the diffusion coefficients were changed with its eigenvalues in order to be adaptive for each pixel. Then an adaptive-driven 3-D tensor matrix was applied to kernel regression denoising schema, in which the correlation among different bands was taken into consideration. The proposed method outperforms better in detail preservation and noise removal.

T. Sakai et al. proposed a Single-image super resolution (SR) reconstruction mistreatment the low-rank matrix recovery and nonlinear mappings. First, the low-rank matrix recovery was used to find out the underlying structures of subspaces spanned by the classified patch options. Second, the low-rank elements of low-resolution (LR) and high-resolution (HR) patch attributes square measure mapped onto high dimensional areas by nonlinear mappings severally. Then the mapped high-dimensional vectors square

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measureprojected onto a unified area, wherever the 2 manifolds created by LR and hour patches severally have similar native pure mathematics and also the SR reconstruction was performed via neighboring embedding. The planned methodology outperforms SR algorithms qualitatively and quantitatively.

T. Zhou et al.proposed a Bilateral random projection (BRP) based mostly low-rank approximation is planned with high speed and higher error bounds. "Go Decomposition" (Go Dec) to approximate the low-rank half L and also the thin half S of a general matrix X=L+S+G is evolved, wherever G was noise. Go Dec was considerably accelerated by mistreatment BRP based mostly approximation. The proposed algorithm discovered the robustness of Go Dec.

D. Castro et al.proposeda neural network based mostly multiscale technique [24] for restoring degraded pictures supported a universal coaching knowledge strategy for image restoration. The projected approach was optimistic and utilized in restoration processes with the profit that it doesn't would like a priori information of the degradation causes.

4. PROPOSED WORK

The block diagram of the proposed work is shown in the following Figure 3

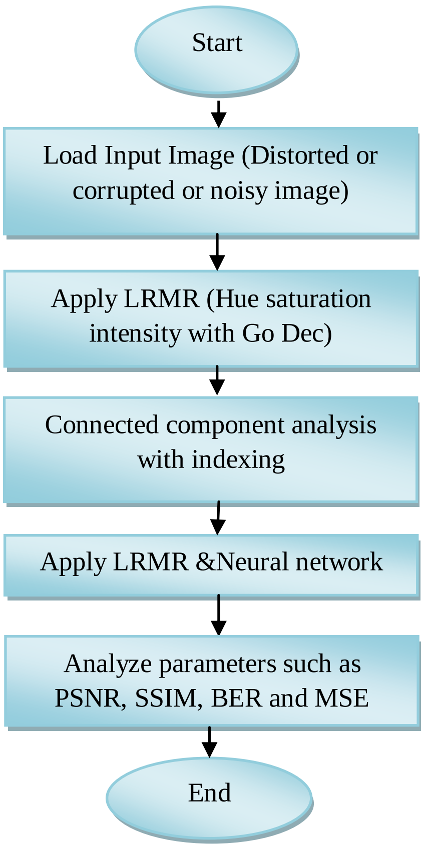

Figure 3: Flowchart of proposed algorithm

This diagram has some important phases of proposed work that are discussed in the following points:

Phase1:Code is developed for loading the hyperspectral image in the database of the MATLAB. This is done for the loading the image pixel value in the workspace of the MATLAB.

Phase2:Code is developed to degrade the image.

Phase3:After that a code is developed for LRMR with HSI and Go-Dec.

Phase4:After those codes is developed for the recovery of missing pixel and neighbouring pixels with connected component analysis and indexing and also resize the image for better restoration.

Phase5: After that code is developed with the combination of LRMR and NN.

Phase6:Finally Results are analyzed between input and restored image using PSNR, SSIM, BER and MSE.

5. PARAMETERS USED

Following are the main parameters that are used to calculate the results of the proposed work. These parameters are:

5.1 Peak Signal to Noise Ratio (PSNR):

PSNR is the ratio value between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

The PSNR of the fusion result is defined as follows:

$$\text{PSNR} = 10\text{X}\log\left(\frac{(f_{\max})^2}{MSE^2}\right)$$

Where fmax is the maximum gray scale value of the pixels in the fused image. Higher the value of the PSNR is better the performance of the fusion algorithm.

5.2 Mean Square Error (MSE):

A commonly utilized reference based assessment metric is the Mean Square Error (MSE). The MSE between a reference image R and a fused image F is given by the

Following equation:

$$\text{MSE} = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\big(R(m,n) - F(m,n)\big)^2$$

Where R (m, n) and F (m, n) are the reference and fused images respectively and M and N are image dimensions. Smaller the value of the RMSE is better the performance of the fusion algorithm.

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5.3 Structure Similarity Index:

This parameter is employed for measure the similarity between 2 pictures. It's enforced to recover on ancient ways like peak S/N (PSNR) and mean square error (MSE).The distinction with reference to different parameters like MSE or PSNR is that it estimates perceived

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

5.4 Bit Error Rate:

It is outlined because the variety of bits received with error divided by the whole variety of bits transmitted. BER is the reciprocal of the PSNR.

$$BER = \frac{1}{PSNR}$$

6. RESULTS AND DISCUSSION

In the following figures, result of proposed algorithm is highlighted.

Figure 4: Original image

Figure 5: Degraded image

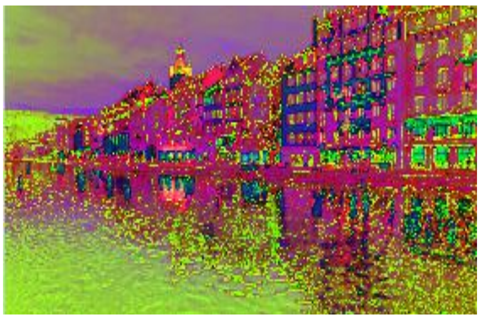

Figure 6: HSI image

Figure 7: Image restored with LRMR with HSI and Go Dec

Figure 8: Image restored with CCA and Indexing

Figure 9: Restored Image

Comparison of MSE between LRMR and LRMR+NN

	LRMR	LRMR+NN
MSE	606.5830	430.8802

Figure 10: MSE values

Comparison of BER between LRMR and LRMR+NN

	LRMR	LRMR+NN
BER	456350	278916

Figure 11: BER values

Comparison of MPSNR between LRMR and LRMR+NN

	LRMR	LRMR+NN
MPSNR	40.3700	43.5745

Figure 12: PSNR values

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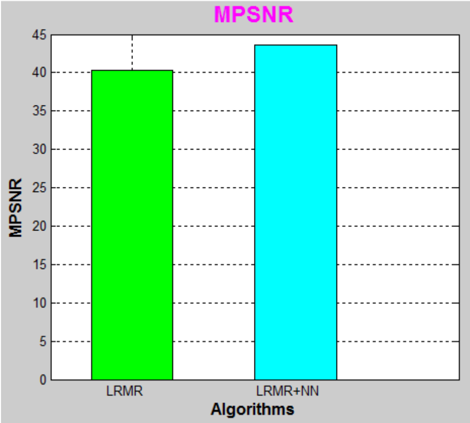

Figure 13: Graphical Representation of PSNR values

Comparison of MSSIM between LRMR and LRMR+NN

	LRMR	LRMR+NN
MSSIM	0.9843	0.9916

Figure 14: SSIM values

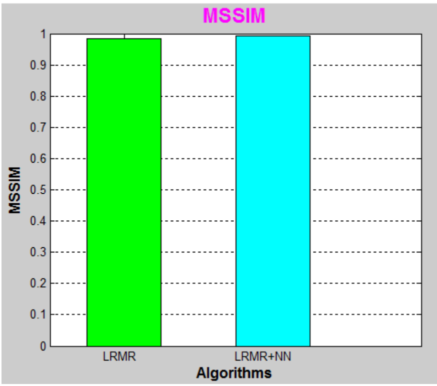

Figure 15: Graphical Representation of SSIM values

7. CONCLUSION

From the above precised discussion, it will be valuable observation into several concepts elaborated, and raise further advances in the area. The exact restoration is directly built upon the nature of the material to be read and by its factors. Present research is directly concerned to the hyperspectral images. From different studies, we have seen that thechoosing of Low Rank Matrix Recovery (LRMR) technique plays a vital role in achievement of hyperspectral image restoration rate. This review well- establishes a complete system that improves the quality of restored image. After that the hyperspectral images are restored by using the proposed techniques i.e. Neural Networks. These materials deliver as a guideand update for readers working in the restoration area.

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REFERENCES

[1] H. zhang and W. He, "Hyper spectral Image Restoration Using Low-Rank Matrix Recovery", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no.8, pp. 4729-4743, Aug. 2014.

[2] Gonzalez, C. Rafael, R. Woods, and S. Eddins, "Digital image processing using MATLAB", *Pearson Education India*, 2004.

[3] K. S. Ettabaa, M. A. Hamdi and R. B. Salem, "SVM for hyper spectral images classification based on 3D spectral signature", *IEEE 1st International Conference on Advanced Technologies for Signal and Image Processing (ATSIP)*, pp. 42-47, March 2014.

[4] L. Damien and S. Bourennane, "Noise removal from hyper spectral images by multidimensional filtering", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 46, no.7, pp. 2061-2069, July 2008.

[5] K. Rao, "Overview of image processing", *Proceedings the National Conference in Readings in image processing*, 1996

[6] R. John, and K. Lulla, "Introductory digital image processing: a remote sensing perspective." (1987): 65-65.

[7] G. Boracchi and A. Foi, "Modelling the performance of image restoration from motion blur", *IEEE transaction on image processing*, vol. 21, no. 8, Aug. 2012.

[8] M. Kaur and K. jain, "Study of image enhancement techniques," International journal of Advance research in computer science and software engineering, vol. 3, issue 3, Apr. 2013.

[9] J. Wright, A. Ganesh, S. Rao, Y. Peng, and Y. Ma, "Robust principal component analysis: Exact recovery of corrupted low-rank matrices via convex optimization", *Proceedings of the conference on Neural Information Processing System*, pp. 2080–2088, 2009.

[10] K. Rong, L. Jiao et al, "Pansharpening Based on Low-Rank and Sparse Decomposition", *IEEE Journal of Applied Earth Observations and Remote Sensing*, vol. 7, no. 12, pp. 4793-4805, Dec. 2014.

[11] S. Maind and P. Wankar, "Research Paper on Basic of Artificial Neural Network", *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 2, no. 1, pp. 96-100, 2014.

[12] A. Hore and D. Ziou, "Image Quality Metrics: PSNR vs. SSIM", IEEE *International Conference on Pattern Recognition*, vol. 34, pp. 2366-2369, 2010.

[13] S. Shirani, "Low bit rate, error resilient image communication using nonlinear pre and post-processing and progressive image transmission", *Proceedings of the International Conference on image processing IEEE*, vol. 3, pp. 553-556, 2002.

[14] K. He, R. Liu et al, "Gaussian noise removal of image on the local feature", *IEEESecond International Symposium on Intelligent Information*

ISSN: 2278 – 1323

Technology Application (IITA), vol. 3, pp. 867-871, 2008.

[16] M. E. Mathew and J. Jeevitha, "An impulse noise cancellation using iterative algorithms", *IEEE International Conference onElectronics and Communication Systems (ICECS)*, pp. 1-6, Feb. 2014.

[17] X. Wang, J. Cao et al, "Research of camera module sensor dead pixel detection", *IEEE Symposium on Electrical & Electronics Engineering (EEESYM)*, pp. 136 – 139, June 2012.

[18] H. Liu, Z. Zhang, et al., "Adaptive tensor matrix based kernel regression for hyperspectral image denoising", *IEEE transaction onGeoscience and Remote Sensing Symposium (IGARSS)*, pp. 4616-4619, 2014.

[19] M. Ye, Q. Liu et al. "A few online algorithms for extracting minor generalized eigenvectors", *IEEE International Joint Conference on Neural Networks (IJCNN)*, pp. 1714-1720, June 2008.

[20] X. Chen and C. Qi, "A single-image super-resolution method via low-rank matrix recovery and nonlinear mappings", *IEEEInternational Conference on Image Processing*, pp. 635-639, Sep. 2013.

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