A Review: Image Restoration using Low Rank Matrix Recovery and Neural Network

Ravneet Sharma[1], Chandandeep Sandhu[2]
Student[1], Chandigarh University, Gharuan, Punjab, India
Assistant professor[2], Chandigarh University, Gharuan, Punjab, India

Abstract - Hyper spectral images (HSIs) 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 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 PSNR, Signal to Noise ratio, Mean Square Error, Bit Error Rate and Accuracy.

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

I. INTRODUCTION

Hyper spectral images are those where each pixel forms an almost continuous spectrum. They have experienced significant success but in practice it suffers from various degradations like blurring due to incorrect focus, movement and other image defects (incorrect exposure and distortion), noise contamination, positioning error and missing data. As a result the visual appearance and the applications of hyper spectral images are severely influenced. Applications like agriculture, forestry, mapping and so on. Therefore HSI restoration is an active area. So, many different denoising methods have been proposed for the restoration of HSIs.

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:

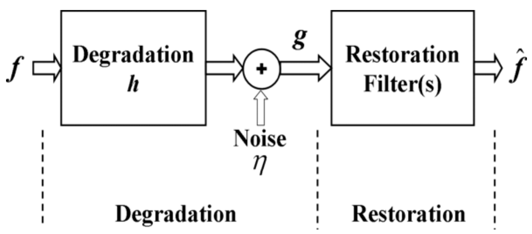

Fig.1: Restoration Model

- Spatial domain
- Frequency domain

II. LOW RANK MATRIX RECOVERY

Low-rank matrix approximation is an important tool for analysis of image, web search and computer vision. It helps in exploiting the low-dimensional data from the high-dimensional data. Unlike the previous image restoration methods, the low-rank matrix approximation based image restoration is that some parts of the clean image are considered as low rank and the main aim is to remove the various types of noises in the noisy or degraded image.

The LRMR model was first proposed by Wright and is idealized as a "robust principal component analysis" (RPCA) problem.

Assuming that a low-rank matrix $L \in R^{m\times n}$ is corrupted by a sparse error matrix $s \in R^{m\times n}$. Then the observed data matrix $D \in R^{m\times n}$ is decomposed as the sum of a sparse matrix and a low-rank matrix i.e. D = L + S **[1]**.

Then the ideal RPCA problem is described as follows: the observed data matrix D, the low-rank matrix L and the sparse error matrix S are unknown and the goal is to recover L.

The formulation of optimization problem is **[2]**

$$\min_{L,S} \operatorname{rank}(L)+\lambda\|S\|_0 \ \text{s.t}\ \ D = L + S \qquad (1)$$

Equation (1) is a highly non-convex optimization problem and efficient solution is unknown. A tractable problem of optimization is obtained by relaxing (1) and replacing the l_0-norm with the l_1-norm and the rank with the nuclear norm **[3]-[4]**, yielding the following convex surrogate:

$$\min_{L,S} \|L\|_* + \lambda\|S\|_1 \ \text{s.t}\ \ D = L + S \qquad (2)$$

Where λ is the regularization parameter used to balance the relative contribution between the nuclear norm and the l_1 norm.

III. NEURAL NETWORKS

Artificial neural networks are composed of interconnecting artificial neurons. The Artificial neural networks are used to acquire the knowledge of biological neural networks and for solving artificial intelligence problems. Artificial neural network algorithms attempt to abstract the complexity and focus on what matter most from an information processing point of view.

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 concept is to lower the aggregate of estimation required to imitate artificial neural networks to allow one to experiment with bigger networks and to line them on larger data sets.

Identification and control, pattern recognition (face identification; object recognition); sequence identification (gesture, speech, handwritten text recognition); medical diagnosis; financial, etc. are the main 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.

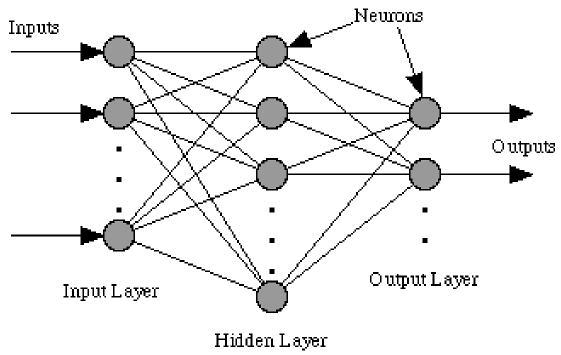

Fig.2: Architecture of NN

In feed-forward networks, the flow of signal is strictly in a feed-forward direction that is from input to output units. The data processing can further expand over multiple layers of units; but there is no feedback connections exist. Feedback connections are present in recurrent networks. The contrary to feed-forward networks is that the dynamical properties of the network are important. For some cases, activation values of the network properties of the network units go through a relaxation process in such a way that the network will change to a stable state in which these activations do not change.

B. Feed Forward Neural Networks

Feed-forward ANNs permit signals to flow in one way only i.e. from input to output. No feedback (loops) is there so the output of any layer does not influence that same layer. The Feed-forward ANNs tend to be straight forward networks that link inputs with outputs. They are mostly used in pattern recognition. This type of organisation is also known as bottom-up or top-down. Single-layer perceptron's, multilayer perceptron's and radial basis function are types of feed forward neural networks.

C. Single Layer Perceptron's

The basic type of neural network is a single-layer perceptron's network which contains a single layer of output nodes and the inputs are directly passed to the outputs through a series of weights. This is considered as the simplest kind of feed-forward network. Then total of the products of the weights and the inputs are computed in each node. If the value is above threshold it takes '1' otherwise it takes '-1'. Neurons with this kind of activation function are also called artificial neurons or linear threshold units. The literature the term perceptron's often refers to networks consisting of one of these units and a similar neuron was described by Warren McCulloch and Walter Pitts in the 1940s. If the threshold value lies between the two then a perceptron's can be developed using 1 and -1 state. Mostly perceptron's have outputs of 1 or -1 with a threshold of 0 and there is some proof that such networks can be lined faster than networks generated from nodes with various activation and deactivation values. Thus Perceptron's can be lined by a simple algorithm that is the delta rule. This calculates the difference between calculated output and sample output and uses them to generate an adjustment to the weights for implementing a form of gradient descent. Single-unit perceptron's are only capable of learning linearly separable 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 class of networks contains multiple layers of computational units which are interconnected in a feed-forward way and in each single layer; each neuron has direct connections with the neurons of the subsequent layer. Therefore the units of these categories of networks apply a sigmoid function as an activation function in different applications. Then universal approximation theorem for neural networks states that every continuous function that maps intervals of real numbers to some output interval can be approximated randomly closely by a multi-layer perceptron's with just one hidden layer. The result holds for limited classes of activation functions for e.g.-the sigmoid functions. The Multi-layer networks use various learning techniques and the most popular being back-propagation. Then output values are compared with the correct values to compute the value of some predefined error-function. With the help of various techniques, the error is fed back via a network. The algorithm arranges the weights of each connection to minimize the value of the error function by some amount. By duplicating this process for a sufficiently more number of training cycles, the network will usually similar to some state where the error of the calculations are minimum. In this case, the network has learned a certain target function and to adjust weights properly a general method for non-linear optimization that is called gradient descent is applied. The derivative of the error function in reference to the network weights are computed and then weights are changed in such a way that the error get minimize. Due to this reason back-propagation can only be used on networks with differentiable activation functions.

IV. PREVIOUS WORK

Ana Paula Abrantes de Castro et al proposed a multiscale image restoration approach based on neural network **[5]** by using multilayer perceptron neural networks trained with duplicate degraded images. The main goal of this scheme is to make the neural network know about space relations of the degraded pixels during restoring the image. First, the degradation is simulated by filtering the image with a low pass Gaussian filter and adding noise to the pixels at pre-established rates. For the learning process, degraded image pixels make the input and non-degraded image pixels make the output. By reconstructing a quasi-non-degraded image in terms of least squared, the neural network performs an inverse operation. The main difference of the proposed approach to previous or existing is that the space relations are obtained from various scales which provide correlated space data to the neural network. The approach tries to develop a simple and easy method that provides better restoration of degraded images without any need of an existing or previous knowledge of the image degradation causes. The multiscale operation is programmed by taking various window sizes around a pixel. In the general phase, the neural network is exposed to satellite degraded images by following the same steps used in degrading the duplicate image of circles. The neural network restoration results show that the proposed approach can be used in restoration processes with the advantage that it does not require previous knowledge of the degradation causes.

Xiaoxuan Chen et al present a method for the reconstruction or restoration of single image super-resolution (SR) by using the low-rank matrix recovery (LRMR) and nonlinear mapping **[6]**. First, to learn the structures of subspaces spanned by the grouped patch features, Low rank Matrix recovery is used. Secondly, the low-rank components of low-resolution and high-resolution patch features are mapped on high-dimensional spaces by non-linear mapping. Then the high-dimensional vectors that are mapped are projected onto a unified space where LR and HR patches respectively construct two manifolds which have similar local geometry. The Super-Resolution reconstruction or restoration is done by using neighbouring embedding. The results show the effectiveness of proposed method and suggest that the proposed method also outperforms other Super-Resolution algorithms more effectively.

Yazeed A. Al-Sbou presents the neural networks as a noise reduction tool **[7]**. The proposed approach uses both mean and median statistical functions for calculating the output pixels of the training pattern of the neural network. The part of the degraded image pixel is used to generate the system training patterns. Different images for testing, noise levels and neighbourhoods sizes of the pixels are used. On the basis of using samples of degraded pixel neighbourhoods as inputs, the output of proposed approach provide a good image denoising performance and promise qualitative and quantitative results of the noisy images in terms of Peak Signal to Noise Ratio, Mean Square Error, etc.

V. CONCLUSION

In this paper, our primary focus is on image restoration. It is hoped that this detailed discussion will be beneficial for various concepts involved and boost further advances in the area. The accurate restoration is directly depending on the nature of the material to be read and by its quality. From various studies we have seen that selection of Low rank matrix recovery (LRMR) and Neural Network (NN) technique plays an important role in performance of restoration. This review establishes a complete system that restores the image properly including pixels, edges and boundaries. This material serves as a guide and update for readers working in the Image restoration area and help them to achieve their motive.

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VI. REFERENCES

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