Restoring SAR Images Using Effective Image Restoration Approach

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ABSTRACT

Landsat 7 Enhanced Thematic Mapper Plus satellite images presents an important data source for many applications related to remote sensing. An effective image restoration method is proposed to fill the missing information in the satellite images. The segmentation of satellite images to find the SLIC super pixels and then to find the image segments. The boundary reconstruction is performed using edge matching to find the area of the missing region. Peak signal to noise ratio and root mean square error are used with boundary reconstruction and without boundary reconstruction to evaluate the quality and the error rate of the satellite images. The results show the capability to predict the missing values accurately in terms of quality, time without need of external information. The values for PSNR has changed from 25 to 90, and RMSE has changed from 180 to 4 in Red Channel of an image. This indicates that the quality of the image is high, and the error rate is low.

KEYWORDS

Gap Filling, Landsat 7 Enhanced Thematic Mapper Plus, Matrix Completion, Remote Sensing, Scan Line Corrector, Segmentation

1. INTRODUCTION

The Landsat 7 scan line corrector (SLC) failed to correct the undersampling of the primary scan mirror on May 31, 2003. On average, about 22% of the total image is missing pixels (Salma et. al., 2017) in each scene. Though NASA has made efforts to correct the SLC malfunction, this has not been successful and the problem prevails. Without the operating SLC, in addition, the areas that have missing pixels are not identical across all multispectral bands. It appears that gaps change positions slightly with spectral bands and produce invalid data in some bands whereas no data in other bands. The non-identical missing pixels in different bands brings out a research problem in trying to identify and fill the data gaps. The Landsat imagery from 1972 to present provides a unique resource for researchers, scientists and users who work in varied domains namely, agriculture, geology, forestry, mapping, regional planning, and global change research. The Enhanced Thematic Mapper Plus was greatly impacted by the failure of the system's SLC. For this, gapping is a typical phenomenon with remote sensing imagery. Remote sensing imagery could have dynamic and diverse characteristics. Thus a variety of image restoration techniques (Francescopaolo *et. al.*, 2018; Kimura *et. al.*, 2011; Rareset.

DOI: 10.4018/IJIRR.289951

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al., 2005) and gap filling techniques (Jiaqing *et. al.*, 2019; Giampaolo *et. al.*, 2019; Mohammed, 2013) could be applied to recover the missing regions.

The proposed system consists of three main parts. The first step is to segment the image using Simple Linear Iterative Clustering (SLIC) (Radhakrishna *et. al.*, 2011) for getting SLIC superpixels and Regionalization with Dynamically constrained agglomerative clustering and partitioning (REDCAP) (Guo, 2007) to get image segments. The second step consists of finding the missing area calculated using Edge Matching Algorithm (Salma *et. al.*, 2017). The third step is used to fill the gaps in the damaged region performed using Accelerated Proximal Gradient Line Algorithm (APGL) (Salma *et. al.*, 2017).

The remaining of the paper is organized as follows: Section 2 gives background on interactive discussion of some related works. Section 3 describes the overall system design, algorithm and detailed description about each module. Section 4 describes about dataset used for the implementation of the proposed framework, results of the experiments conducted, test cases, performance evaluation. Section 5 describes about the results of proposed system with existing system. Section 6 discusses about the conclusion.

2. LITERATURE SURVEY

Salma *et. al.*, (2017) proposed an optimal segmentation by resizing the image and the image is enhanced filtering namely gaussian filtering to remove various disturbance and impulse noise affected during the acquisition process. The dataset consists of synthetic images and real images. The synthetic images contain noise which should be preprocessed before filling the gaps. The real image is the correct image. The synthetic images and real images are compared to find the quality of the reconstructed image.

Radhakrishna *et. al.*, (2011) proposed a k-means clustering approach to efficiently generate Super Pixels. SLIC adheres when compared to RG and WT algorithm. It is faster and more memory efficient, improves segmentation performance. The number of distance calculations in the optimization is dramatically reduced by limiting the search space to a region proportional to the super pixel size. This reduces the complexity to be linear in the number of pixels N and independent of the number of super pixels k . SLIC is similar to the approach used as a pre-processing step for depth estimation described in which was not fully explored in the context of super pixel generation.

Guo (2007) proposed a Regionalization with dynamically constrained agglomerative clustering and partitioning is a Dynamic region Clustering algorithm. SLIC super pixels is sent as an input and processing is done using REDCAP algorithm to get Image segments. This algorithm makes use of attribute differences and adjacency relationship among different regions to merge regions. It uses Full order CLK rule. After minimum spanning tree is generated, it is cut to generate series of subtrees. Regions in the subtree are merged into cluster.

Mai *et. al.*, (2019) proposed a method based on optimization technique to detect slow moving landslides in time series of displacement field generated by satellite images. Sparse optimization is applied simultaneously on the 3-D data set in space as well as in time. The proposed method takes into account the distinctive signal physical properties in space and time by enforcing a sparse representation by blocks in space but a continuing and monotonous representation in time of the landslides. The performance of this approach is tested by applying it both on synthetic data and on a time series of displacements fields over 16 dates in the Colca Valley, Peru. This detection presents commission and omission errors for landslides of 29% and 14%, respectively, using a medium resolution data set of optical satellite images.

Yangyan *et. al.*, (2019) proposed a rapid development of various technologies of satellite sensor, synthetic aperture radar called SAR image has been an important source of data in the application of change detection. The main idea of our method is to generate the classification results directly from the original two SAR images through a CNN without any preprocessing operations, which also

eliminate the process of generating the difference image, thus reducing the influence of the DI on the final classification result. In CNN, the spatial characteristics of the raw image can be extracted and captured by automatic learning and the results with stronger robustness can be obtained. The basic idea of the proposed method includes three steps: it first produces false labels through unsupervised spatial fuzzy clustering. Then we train the CNN through proper samples that are selected from the samples with false labels. Finally, the final detection results are obtained by the trained convolutional network. Although training the convolutional network is a supervised learning fashion, the whole process of the algorithm is an unsupervised process without prior knowledge.

Kalamrajuet.al.,(2019)estimation helps in better understanding of atmospheric dynamics and also plays a key role in weather forecasting. It has been a challenging task because of the nonrigid motion of clouds and cyclones. A modified Weighted Ensemble Transform Kalman Filter-based data assimilation technique is proposed for accurate flow vector estimation at each pixel directly from satellite generated infrared images of clouds/cyclones. This method provides clear visualization of both local and global motion with spatial and temporal consistencies very efficiently even in the case of splitting and merging of clouds or over long tracks. One of the key abilities of proposed method is in forecasting applications and also for generating motion vectors in the absence of data in real scenarios, even without the usage of the existing complex weather models.

Sina et.al.,(2019)addresses the problem of training a deep neural network for satellite image segmentation so that it can be deployed over images whose statistics differ from those used for training. The convolutional encoder–decoder network able to learn visual representations of increasing semantic level as its depth increases, allowing it to generalize over a wider range of satellite images. The proposed two additional methods to improve the network performance over each specific image to be segmented. First, they observe that updating the batch normalization layers' statistics over the target image improves the network performance without human intervention. Second, they showed that refining a trained network over a few samples of the image boosts the network performance with minimal human intervention. The results of three data sets of satellite images, showing the state-of-the-art performance in binary segmentation of previously unseen images and competitive performance with respect to more complex techniques in a multiclass segmentation task.

Huihuiet.al., (2014) address the problem that shadows in high-resolution satellite images are usually caused by the constraints of imaging conditions and the existence of high rise objects especially in urban areas. To alleviate the shadow effects in high-resolution images for their further applications, a novel shadow detection algorithm based on the morphological filtering and a novel shadow reconstruction algorithm based on the example learning method. In the shadow detection stage, an initial shadow mask is generated by the thresholding method, and then, the noise and wrong shadow regions are removed by the morphological filtering method. The shadow reconstruction stage consists of two phases: the example-based learning phase and the inference phase. During the inference phase, the underlying land cover pixels are reconstructed from the corresponding shadow pixels by adopting the Bayesian belief propagation algorithm to solve the MRF of classification by comparing the classification maps of images before and after shadow reconstruction.

Chao-Hung et.al., (2013) approach based on information cloning is introduced. The approach removes cloud-contaminated portions of a satellite image, and then reconstructs the information of missing data utilizing temporal correlation of multitemporal images. The basic idea is to clone information from cloud-free patches to their corresponding cloud-contaminated patches under the assumption that land covers change insignificantly over a short period of time. The patch-based information reconstruction is mathematically formulated as a Poisson equation and solved using a global optimization process.

Tohet.al.,(2010) approach is based on the affine rank minimization problem, which consists of finding a matrix of minimum rank subject to linear equality constraints, has been proposed in many areas of engineering and science. A specific rank minimization problem is the matrix completion problem, which recovers a (low-rank) data matrix from incomplete samples of its entries. A recent

convex relaxation of the rank minimization problem minimizes the nuclear norm instead of the rank of the matrix. Another possible model for the rank minimization problem is the nuclear norm regularized linear least squares problem. This regularized problem is a special case of an unconstrained nonsmooth convex optimization problem, in which the objective function is the sum of a convex smooth function with Lipschitz continuous gradient and a convex function on a set of matrices. They used an accelerated proximal gradient algorithm, which terminates in $O(1/\sqrt{2})$ iterations with an 2 -optimal solution, to solve this unconstrained nonsmooth convex optimization problem, and in particular, the nuclear norm regularized linear least squares problem.

In conclusion, in this paper an effective Image Restoration approach is proposed. A specific comparative study of the proposed Image Restoration approach with the recent development in this domain has been carried out as shown in Table 1.

In this work, Image Restoration is performed to restore the missing information with the captured image. The aim is to bring the image towards what it would have been recorded with degradation. It is an objective processing technique and restores using the prior knowledge of degradation. The proposed Image Restoration approach works to fix the image to get back to real and true image.

3. EXPERIMENTAL DESIGN

This section discusses the overall system and the process involved in the proposed Image Restoration system. Missing area indicates that damaged region because of the failure of Scan Line Corrector and loss of 22% of data is indicated by the Missing region. Filling Gaps in Landsat 7 Satellite Images, Superpixel Based Segmentation, Dynamic Region Clustering and Filling Missing Gaps are discussed in the sub sections.

3.1 Filling Gaps in Landsat 7 Satellite Images

An image restoration method is proposed to fill the missing information gap in the Landsat 7satellite image. The segmentation is performed using the superpixels (Mi *et. al.*, 2018) obtained by adapting SLIC superpixels algorithm. The obtained SLIC superpixels are merged using the dynamic clustering algorithm namely REDCAP algorithm. In the process of merging, the LV value and the ROC-LV value are taken into consideration. Boundary reconstruction is accomplished using edge matching using two edge couples. Edge couples on both sides of the information must be similar. Similarly, the magnitude of the local gradient must be similar. Further, the edges must keep one side inside damaged region and other outside damaged region so that they can interact with each other. Then matrix completion is used for filling gaps and is achieved by adopting APGL. The results are compared using Landsat 7Synthetic images and Landsat 8 Real images using PSNR and RMSE values.

Figure 1 explains the overall block diagram of the proposed satellite image restoration system. The dataset consists of both real and synthetic images. The input images are preprocessed by performing

Table 1. Comparison with recent developments

Parameter	Effective Image Restoration Approach	Recent Development in this Domain
1. Noise for Parameter Extraction	Noise present in Landsat 8 was removed using Gaussian Filtering to have a clear view of where to perform restoration.	Parameter Extraction was difficult to extract simulation parameters from SAR image due to the presence of noise.
2. Edge Enhancement Generative Adversarial Network for SAR images	Missing Pixels are filled using Accelerated Proximal Gradient Line Algorithm to form	Feature extraction was tough because it was eroded with artifacts and noise.
3. PSNR after image Restoration	91.55 dB	24.39 Db

Figure 1. Block diagram of image restoration system

basic preprocessing operations namely, image resizing, image enhancement and filtering. Gaussian filtering is used for filtering the satellite images. The preprocessed image is segmented using SLIC and REDCAP algorithm. The Boundary Reconstruction is performed using Edge Matching Algorithm and Matrix Completion used APGL algorithm to fill the gaps.

3.2 Superpixel Based Segmentation

SLIC used by Radhakrishna *et. al.*, (2011) adapts a *k*-means clustering approach to efficiently generate superpixels. It adheres to the boundaries as well or better than previous methods. This is faster and more memory efficient, improves segmentation performance, and is straightforward to extend to superpixel generation. The number of distance calculations in the optimization is dramatically reduced by limiting the search space to a region proportional to the superpixel size.

SLIC algorithm works in CIELAB color space. The first step is initialization step where each pixel are sampled on a regular grid spaced *S* pixels apart. The grid interval is computed using $S = \sqrt{N/k}$. The cluster centers are updated to seed locations corresponding to the lowest gradient position in a 3 X 3 neighborhood. This reduces further the chance of seeding a superpixel with a noisy pixel. The next step is the assignment step, in which each pixel *i* is associated with the nearest cluster center whose search region overlaps its location. The distance calculations involved, D' are carried out using equations (1). The superpixel is the region obtained in the $2S \times 2S$ around the superpixel center:

$$d_c = \sqrt{(l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2}$$

$$d_s = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$$

$$D' = \sqrt{\left(\frac{d_c}{c}\right)^2 + \left(\frac{d_s}{N_s}\right)^2} \quad (1)$$

The last step which is the update step consist of each pixel has been associated to the nearest cluster center, an update step adjusts the cluster centers to be the mean vector of all the pixels belonging to the cluster. The assignment and update steps can be repeated iteratively until the error converges. At the end of the SLIC clustering, some orphaned pixels that do not belong to the same connected components as their seed points, remain. Such pixels are assigned the label of the nearest seed point based on connected components concept.

3.3 Dynamic Region Clustering

REDCAP algorithm is a dynamic region clustering algorithm. This was proposed by Guo (2007). This algorithm utilizes the attribute difference and adjacency relationship among different regions to merge regions. Regionalization is to divide a large set of spatial objects into a number of spatially contiguous regions while optimizing an objective function, which is normally a homogeneity or heterogeneity measure of the derived regions. It is done by using Full Order CLK Rule. Full Order CLK Rule is it need a matrix to keep the distance among existing clusters. The input which is the SLIC superpixels undergoing REDCAP algorithm yields a set of image segments.

The optimal segmentation number can be found by LV and ROC-LV using ESP tool. The Estimation of Scale Parameter (ESP) tool is used for calculating SD from an $n \times n$ moving window, derived from objects obtained through segmentation. The graphics of LV are used to evaluate the appropriate scale parameter, relative to the data properties of the scene. Appropriate scales of the image are in the range of scale when the graphics of LV are smooth. To assess the dynamics of LV from one object level to another, the measurement called ROC-LV proposed in the ESP tool is used. The combined ESP method with REDCAP algorithm is used for region merging.

The mean value of standard deviation of spectral attribute of the pixels with in the window is calculated using equation (2):

$$LV = \frac{1}{N} \sum_{r=1}^N \sqrt{\frac{1}{n_r} \sum_{j=1}^d \sum_{i=1}^{n_i} (x_{rj} - \bar{x}_{rj})^2} \quad (2)$$

Accessing the dynamic LV from one object level to another a measurement called ROC-LV is calculated using equation (3) and plotted on ESP tool:

$$\left[\frac{L_N - L_{N+1}}{L_{N+1}} \right] \times 100 \quad (3)$$

3.3.1 Edge Matching Based on Missing Region

Boundary Reconstruction is used to get the image structure of the missed area. The types of edges taken into consideration are given. Using these the edge matching method arrives at the image structure of the missed area.

3.3.2 Types of Edges

- **Matched edge:** It consist of the edges which are closely related to each other. The grey value of the point in the radian is computed using equation (4):

$$\lambda^{pi} = \frac{w_1 \lambda^{p1} + w_2 \lambda^{p2}}{w_1 + w_2} \quad (4)$$

- **Coupled edge:** It consist of the edges which are moderately related to each other. The grey value of the point in the radian is computed using equation (5):

$$\lambda^E = \frac{W_1^a \lambda^{p1} + W_2^a \lambda^{p2}}{W_1^a + W_2^a} \quad (5)$$

- **Single edge:** It consist of edges which are unrelated to each other. The Euclidian distance between point E and pi (i∈ 1, 2)) and computed using equation (6):

$$\lambda^{pi} = \frac{W_1^b \lambda^{p1} + W_E^b \lambda^{p2}}{W_1^b + W_x^b} \quad \lambda^{pi} = \frac{W_1^c \lambda^{p1} + W_E^c \lambda^{p2}}{W_1^c + W_E^c} \quad (6)$$

In this work, Matched Edge is considered so that it gets exactly matched with the input image for image restoration. The Edge matching is performed according to the following rules: The two Luminance values on both sides of the edge in each edge couple should be similar. The Magnitude of the local gradient of both the edges should be similar and the Edges have to keep one side inside the damaged region and other outside the damaged region so they can easily interact with the damaged region.

The input to our algorithm is an image and an artefact mask. In the first step, edges are detected around the artefact, based on the contours of the segments that result from a matched edge, coupled edge, as well as single edge. The object edges are extracted in clockwise order, from a point of view lying inside the artefact. Simple edge features are extracted for each edge, such as the luminance values on both sides of the edge, and the local gradient magnitude along the edge. Only relevant edges are then kept for the next steps. In the second step, we try to recover the structure of the image within the artefact area. Finally, in the third step, the artefact is restored by inpainting, taking into account the recovered image structure.

3.4 Filling Missing Gaps

Missing area indicates that damaged region because of the failure of Scan Line Corrector and loss of 22% of data is indicated by the Missing region. The matrix completion method is used for filling the rest of the missing information in the damaged region. The matrix completion method is formulated using Accelerated Proximal Gradient Line Algorithm.

Algorithm for Accelerated Proximal Gradient Line

Let $\mu > 0$ be a fixed regularization parameter and $\eta \in (0,1)$ be a given constant.

Choose $X^0 = X^{-1} \in^k R^{m \times n}$. Set $t^0 = t^{-1} = 1$ and $T^0 = L_f$.

For $k=0,1,2,\dots$, generate X^{K+1} according to the following iteration:

Step 1: Set $Y^k = X^k + \frac{t^{k-1} - 1}{t^k} (X^k - X^{k-1})$

Step 2: Set $\hat{T}_0 = \eta T^{k-1}$
For $j=0, 1, 2, \dots$

Set $G = Y^k - (\hat{T}_j)^{-1} A^* (A(Y^k) - b)$, compute $S_{\hat{T}_j}(G)$

If $F(S_{\hat{T}_j}(G)) \leq Q_{\hat{T}_j}(S_{\hat{T}_j}(G), Y^k)$,

Set $T^k = \hat{T}_j$, stop;

else,

$\hat{T}_{j+1} = \min\{\eta^{-1} \hat{T}_j, L_f\}$

end

end

Step 3: Set $X^{k+1} = S_{T^k}(G)$

Step 4: Compute $t^{k+1} = \frac{1 + \sqrt{1 + 4(t^k)^2}}{2}$

The first technique for accelerating the convergence of APGL is the, linear search like procedure in step 2 of the APGL algorithm has an important advantage. The equation T^k has the form $T^k = \eta^{L_k} L_f$ for some non-negative integer L_k or each k. Thus T^k is typically smaller than L_f and implies that the vector $(\sigma - \frac{\mu}{T^k})$ would have fewer positive components when computing $S_{T^k}(G)$. Thus iterating X^{k+1} would have low rank for faster convergence.

The second technique for accelerating the convergence of APGL is the, continuation technique. When updating the current point X^k at iteration k the result is $S_{T^k}(G)$. This is the main computation in APGL Algorithm. However the singular values are greater than the regularized parameter, $\frac{\mu}{T^k}$. If the parameter is large, then the number of singular values to be evaluated are smaller. But the target parameter $\bar{u}$ is chosen to be smaller number. Thus this motivates us to use the continuation technique.

The third technique for accelerating the convergence of APGL is the, truncation technique. The algorithm without any accelerating techniques the iterate X^k is not a low rank before the final phase of the algorithm, but the number of positive singular values of X^k would separate it into two clusters. The first cluster having much larger mean value than that of the second cluster. The number of singular values in the first cluster has a good estimate on the rank of the low rank optimal solution. The second cluster of smaller positive singular values can attribute to the presence of the noise. Thus the second cluster is discarded without affecting the convergence of APGL algorithm.

4. EXPERIMENTAL RESULTS

The proposed image restoration system is implemented in MATLAB since it allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages. This project is implemented using MATLAB R2018a version. Importing the images are done by typing the URL. In image processing, noise in a digital image arises during image acquisition and also during transmission. Different types of noise include speckle, Gaussian, salt-and-pepper and more. Special effects of the noises can be seen. Since

SLIC works in colorspace, `makeform ()` is used for converting RGB to CIELAB color space and is applied using `applycform()`. The graphs are plotted using the various predefined functions like for line graph it is indicated as `-o` using the `plot()`. The file is saved using `.m` extension for further execution.

4.1 Dataset Description

Dataset consist of both synthetic and real images. Synthetic images are color images used in three channels namely, red, green, and blue. The real image is a Landsat 8 satellite image downloaded from united states geological survey for earth resource observation and science center with path:200 and row:36. It is located in north of Africa. The images are downloaded with latitude value and longitude value of (32.71,-6.04) respectively. The dataset has been downloaded from <https://earthexplorer.usgs.gov/>.

The Figure 2 describes that for a preprocessed satellite image after undergoing the SLIC algorithm yields magnified SLIC superpixels.

Figure 3 shows the image segments obtained for two different satellite images. The magnified superpixels undergo REDCAP algorithm to get the image segments.

The figure 4 describes the output of edge matching. When compared with input image of edge matching, which is the output of REDCAP, in matched edge, there is no relation. In coupled edge edges are moderately related and in single edge the edges are totally unrelated.

Figure 5 describes the output obtained after filling missing gaps. The missing regions are restored using APGL. The above images describes which in land area and grass area.

5. RESULT ANALYSIS

This section presents the experimental analysis. The image restoration system is experimentally evaluated using evaluation parameters, namely, peak signal-to-noise ratio and root mean squared error. The values obtained for these parameters and the discussion on the results are presented in this section. We have illustrated the effectiveness of our Image Restoration approach using Table 2 and 3. We have shown the effectiveness of the Boundary Reconstruction if used by comparing it with the

Figure 2. Superpixels obtained by SLIC

Figure 3. Image Segments of REDCAP

Figure 4. Edge Matching based on Missing Region

values of the same images without Boundary reconstruction. Further, to illustrate the effectiveness of the work, we have compared with Landsat 8 real images.

5.1 Peak Signal to Noise Ratio

This computes the term peak signal-to-noise ratio (PSNR) using equation (7) and is an expression for the ratio between the maximum possible value of a signal and the power of distorting noise that affects the quality of its representation:

$$PSNR = 10 \log_{10} \left(\frac{R^2}{MSE} \right) \quad (7)$$

5.2 Root Mean Squared Error

This root mean squared error (RMSE) computes the root of the expected squared error between the predicted time values and the ground truth using equation (8):

Figure 5. Filling missing gaps

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (t_i - \hat{t}_i)^2} \quad (8)$$

The PSNR and RMSE values are computed using the equations from the experimental results obtained. The PSNR and RMSE values for the synthetic images are tabulated in Table 2 and the PSNR and RMSE values for the real images are tabulated in Table 3.

The figure 6 shows the PSNR values obtained for various images represented by their image number. The graph indicates that PSNR values obtained for synthetic images using boundary reconstruction is high when compared to that of real images. The figure 7 shows the RMSE values obtained for various images represented by their image number. The graph indicates that error rate is less for the case using boundary reconstruction. Thus for synthetic images the quality of the image is high and the error rate is low.

In figure 8 the graph shows the PSNR values obtained for various real images represented by their image number. The graph indicated that PSNR values for real images using boundary reconstruction is less and in figure 9 error rate is high when compared to that of synthetic images.

6. CONCLUSION

A novel image restoration approach for filling gaps based on SLIC segmentation and matrix completion reinforced by edges restoration is proposed. The problem of gaps in Landsat 7 SLC-off ETM+ images was addressed by the novel image restoration method proposed. Segmentation is done using SLIC for detecting the superpixels and a dynamic clustering algorithm namely REDCAP algorithm is used for getting the image segments. Matrix completion method based on Accelerated Proximal Gradient Line algorithm is used for filling the gaps in satellite images. Experiments are carried out using both

Table 2. PSNR and RMSE for synthetic images

Synthetic Image	PSNR without Boundary Reconstruction	PSNR with Boundary Reconstruction	RMSE without Boundary Reconstruction	RMSE with Boundary Reconstruction
R=25.6082 G=25.61 B=25.6086	R=91.55 G=54.52 B=53.08	R=180.16 G=179.90 B=180.14	R=4.57 G=0.23 B=0.32
R=25.60 G=25.62 B=25.61	R=50.75 G=39.17 B=47.25	R=180.10 G=179.61 B=180.07	R=0.55 G=7.93 B=1.23
R=25.87 G=25.69 B=25.65	R=86.78 G=67.30 B=62.94	R=169.59 G=176.75 B=178.16	R=1.37 G=0.01 B=0.03
R=25.60 G=25.62 B=25.61	R=81.70 G=50.06 B=54.40	R=180.14 G=179.62 B=179.82	R=4.42 G=0.64 B=0.23

synthetic and real satellite images and the quality of the restored images are evaluated using peak signal to noise ratio and root mean square error values. The results show that for the reconstructed satellite images quality is high and the error rate is low when comparing reconstructed Landsat 7 synthetic images with corresponding Landsat 8 real images. The PSNR value for red channel has reached 91.55, and ranges between 50.75 and 91.55. RMSE of 0.01 is achieved in green channel and the values ranges between 0.01 and 7.93. This indicates that the quality of the restored image obtained by the proposed image restoration approach is high and the corresponding error rate experienced is less. In future, the problem of damaged area due to the presence of clouds in the satellite image, which means a very large damaged area could be studied. We could experiment different approaches with different methodology.

Table 3. PSNR and RMSE for real images

Real Image	PSNR with Boundary Reconstruction	PSNR without Boundary Reconstruction	RMSE without Boundary Reconstruction	RMSE with Boundary Reconstruction
R=25.74 G=25.733 B=25.730	R=49.00 G=49.38 B=49.63	R=174.64 G=175.04 B=175.16	R=0.00 G=0.75 B=0.71
R=25.66 G=25.655 B=25.654	R=48.77 G=32.31 B=33.72	R=177.99 G=178.24 B=178.21	R=0.86 G=38.42 B=27.76
R=25.66 G=25.6598 B=25.6593	R=90.04 G=93.31 B=88.37	R=177.95 G=178.03 B=178.05	R=6.48 G=3.05 B=9.53
R=25.648 G=25.643 B=25.642	R=59.03 G=31.55 B=32.47	R=178.51 G=178.71 B=178.72	R=0.08 G=45.83 B=37.10

Figure 6. PSNR for Synthetic images

Figure 7. RMSE for synthetic images

Figure 8. PSNR for real images

Figure 9. RMSE for real images

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