

SLIC-Based Cloud Removal Approach with Inpainting for Landsat 8 SAR Images

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ABSTRACT

Clouds that exist in optical remote sensing images can degrade their applicability for earth observation. Ground-cover information is degraded by thin clouds or even completely occluded by thick clouds, which limits further analysis and applications. Thus, a SLIC-based cloud removal approach is formulated for clustering the similar superpixels and forming column stack. Group sparsity constrained robust principal component analysis is used to detect cloud and generate a column stack mask. Discriminative robust principal component analysis is conducted to remove clouds. Finally, inpainting is performed by finding the similar patches to obtain the gaps filled. The experimental results of reconstructed Landsat 8 real images are compared with the Landsat 7 real images using PSNR and RMSE. The values for PSNR are varying from 25 in Landsat 7 real images to 90 in Landsat 8 reconstructed real images in green channel, and RMSE has changed from 175 in Landsat 7 real images to 3 in red channel. This indicates that Landsat 8 reconstructed real images have greater quality and the error rate is lower.

KEYWORDS

Discriminative Robust Principal Component Analysis, Group Sparsity Constrained Principal Component Analysis, Inpainting, Landsat 8 Enhanced Thematic Mapper Plus, Simple Linear Iterative Clustering

1. INTRODUCTION

Clouds which exist in optical remote sensing images with high possibility can degrade limiting to their applicability for earth observation. The Enhanced Thematic Mapper Plus (ETM+) land scenes are reported to be about 35% cloud covered by Yongjun Zhang et.al (2019) globally. Ground cover information is degraded by thin clouds or even completely occluded by thick clouds, which remarkably limits further analysis and applications of such images. In particular, the effect of clouds varies according to the thickness. Thin clouds allow part of underlying objects being observed, which are often ambiguous and could be fairly subtle to formulate and solve such cloud associated problems. On the other hand, thick clouds allow no groundcover information being observed, thus solutions are required urgently to overcome such a challenging problem.

However, because of the significant influence of atmospheric density and cloud layer change on remote sensing processes, most of the remotely sensed images encounter different levels of cloud contamination. The attenuation and even loss of some image information caused by cloud not only reduces the quality and utilization of remote sensing data dramatically but also causes the difficulty of the analysis and application of remote sensing images. In order to improve the usability of remote sensing images (Hemalatha et. al., 2017), it is indispensably essential to conduct cloud detection and removal before any task-specific remote sensing analysis.

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In recent years, a large number of cloud detection methods have been proposed. For moderate-spatial resolution and low-spectral-resolution sensors like Landsat, many automated cloud detection algorithms have been developed based on a single Landsat image. Y. Shen et.al (2016) proposed an assessment using the measurement that is traditionally done in remote sensing studies is impossible because of the spatiotemporal variability of clouds. An alternative approach is to find a reference image from the same remote sensor, and the image is cloud free. In addition, the image should be of the closest acquisition or near anniversary dates such that the temporal/seasonal variation is minimized.

Since the algorithm is applied to the entire study area, we not only need to assess the algorithm's ability to remove clouds. S. Qiu et.al (2017) proposed Clouds and cloud shadows are a pervasive, dynamic, and unavoidable issue in Landsat images, and their accurate detection is the fundamental basis for analyzing LTS. Many cloud and/or cloud shadow detection algorithms have been proposed in the literature. For cloud detection, most approaches are based on a single-date Landsat image, which rely on physical-rules or machine-learning techniques. Fei Wen et.al (2017) proposed that the inevitable existence of clouds and their shadows in optical remote sensing images, certain ground-cover information is degraded. A two-pass robust principal component analysis (RPCA) framework for cloud removal in the satellite image sequence was used. First, a plain RPCA is applied for initial cloud region detection, followed by a straightforward morphological operation to ensure that the cloud region is completely detected. Subsequently, a discriminative RPCA algorithm is proposed to assign aggressive penalizing weights to the detected cloud pixels to facilitate cloud removal and scene restoration.

The main contributions in this paper are: The proposed concept is formulated using Simple Linear Iterative Clustering (SLIC) for clustering the similar superpixels by Radhakrishna Achanta et.al (2011) and form a Column Stack. The cloud detection and removing is proposed by Fei Wen et.al (2018) which can be formulated using Group sparsity constrained Robust Principal Component Analysis (GRPCA) and Discriminative Robust Principal Component Analysis (DRPCA). The input image sequence of the same area obtained at different times can be misaligned. First, simple linear iterative clustering (SLIC) superpixel segmentation and arranging each image to a column of a matrix are conducted as preprocessing. Then, Group-sparsity constrained RPCA (GRPCA) combined with geometrical transformation proposed by Yongjun Zhang et.al (2019) is applied to detect cloud and shadow regions initially and also generate a well aligned image sequence.

2-D Transformation proposed by Y. Peng et.al (2012) explained that the satellite images will get into a well aligned satellite images. Finally, Discriminative RPCA (DRPCA) is conducted to remove clouds and shadows given by Yongjun Zhang et.al (2019) to obtain a sequence of cloud removed images. The reconstruction is carried out using $\log \det(\cdot)$ low-rank regularization method explained by Jiaqing Miao et.al (2019). The Landsat 8 Cloud free Real images are compared with Gap filled Landsat 7 satellite image using the performance metrics namely Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), to evaluate the quality and error rate of the satellite images.

The rest of the paper is organized as follows: Section 2 summarizes discussion on works related to cloud removal and inpainting. Section 3 describes the overall system design, algorithm and detailed description about each module. Section 4 describes the dataset used for the implementation of the proposed framework, results of the experiments conducted and test cases. Further it presents the performance evaluation and discusses the inferences drawn from the results of proposed system in comparison with the existing system. Section 5 concludes the work and provides limitations and scope for future work.

2. LITERATURE WORK

Radhakrishna Achanta et.al (2011) proposed a method for computer vision applications have come to rely increasingly on superpixels in recent years, but it is not always clear what constitutes a good superpixel algorithm. In an effort to understand the benefits and drawbacks of existing methods, a new superpixel algorithm, simple linear iterative clustering (SLIC), which adapts a k-means clustering approach to efficiently generate superpixels is used.

Liang Yan *et.al* (2020) explains about the Pixel-level classification for very high resolution (VHR) images is a crucial but challenging task in remote sensing. However, since the diverse ways of satellite image acquisition and the distinct structures of various regions, the distributions of the same semantic classes among different data sets are dissimilar. Therefore, the classification model trained on one data set may collapse, when it is directly applied to another one. To solve this problem, a triplet adversarial domain adaptation (TriADA) method that jointly considers both domains to learn a domain-invariant classifier by a novel domain similarity discriminator is used.

Yongjun Zhang *et.al* (2019) proposed a method for Clouds and accompanying shadows, which exist in optical remote sensing images with high possibility, can degrade or even completely occlude certain ground-cover information in images, limiting their applicabilities for Earth observation, change detection, or land-cover classification. A course to fine grained superpixels where first decompose the observed cloud image sequence of the same area into the low-rank component, group-sparse outliers, and sparse noise, corresponding to cloud-free landcovers, clouds, and noise respectively. Subsequently, a discriminative robust principal component analysis algorithm is utilized to assign aggressive penalizing weights to the initially detected cloud pixels to facilitate cloud removal.

Yigang Peng *et.al* (2012) proposed a method for the problem of simultaneously aligning a batch of linearly correlated images despite gross corruption. This method seeks an optimal set of image domain transformations such that the matrix of transformed images can be decomposed as the sum of a sparse matrix of errors and a low-rank matrix of recovered aligned images.

Qiang Zhang *et.al* (2018) explains about the internal malfunction of satellite sensors and poor atmospheric conditions such as thick cloud, the acquired remote sensing data often suffer from missing information, i.e., the data usability is greatly reduced. A novel method of missing information reconstruction in remote sensing images is used. The unified spatial-temporal-spectral framework based on a deep convolutional neural network (CNN) employs a unified deep CNN combined with spatial-temporal-spectral supplementary information. In addition, to address the fact that most methods can only deal with a single missing information reconstruction task, the proposed approach solves typical missing information reconstruction tasks.

Zhenfeng Shao *et.al* (2019) explains the Cloud detection in remote sensing images is a challenging but significant task. Due to the variety and complexity of underlying surfaces, most of the current cloud detection methods have difficulty in detecting thin cloud regions. In fact, it is quite meaningful to distinguish thin clouds from thick clouds, especially in cloud removal and target detection tasks. Method based on multi-scale features convolutional neural network (MF-CNN) is used to detect thin cloud, thick cloud, and non-cloud pixels of remote sensing images simultaneously. Landsat 8 satellite imagery with various levels of cloud coverage is used to demonstrate the effectiveness of our proposed MF-CNN model.

Wenyuan Li *et.al* (2014) explains about the Cloud detection, as an important preprocessing operation for remote sensing (RS) image analysis, has received increasing attention in recent years. Most of the previous cloud detection methods consider the detection as a pixel-wise image classification problem, cloud versus background, which inevitably leads to a category-ambiguity when dealing with the detection of thin clouds.

Jiaqing Miao *et.al* (2019) proposed a method of a novel inpainting algorithm for recovering the ETM+ SLC-off images. The two slopes of the boundaries of each missing stripe were extracted through the Hough transform, ignoring the slope of the edge of the strip that overlaps the edge of the image. An adaptive dictionary was then developed and trained using ETM+ SLC-on images acquired before May 31, 2003 so that the physical characteristics and geometric features of the ground coverage of the data-missing strips can be considered during recovery. The algorithm was tested using the simulated ETM+SLC-off images created from a multiband ETM+SLC-on image file and compared to the high accuracy low-rank tensor completion (HaLRTC), logDet, and tensor nuclear norm (TNN) algorithms.

Luca Lorenzi *et.al* (2011) proposed a technique for missing data in very high spatial resolution (VHR) optical imagery take origin mainly from the acquisition conditions. Their accurate reconstruction represents a great methodological challenge because of the complexity and the ill-posed

nature of the problem. In this work, they presented three different solutions, all based on the inpainting approach, which consists in reconstructing the missing regions in a given image by propagating the spectro-geometrical information retrieved from the remaining parts of the image.

In conclusion, all available methods essentially recover only one target cloud image at each time, no matter how the relationship between contaminated pixels and cloud-free pixels is exploited. Though visually plausible recovery results can be generated by these methods. Hence, we propose a batch-processing approach based on RPCA framework to remove cloud from image sequence with high efficiency and accuracy. We introduce a 2-D affine transformation model to enable our method to handle misaligned images of the sequence. The detailed design of the proposed SLIC based cloud removal approach is elaborated in the following section.

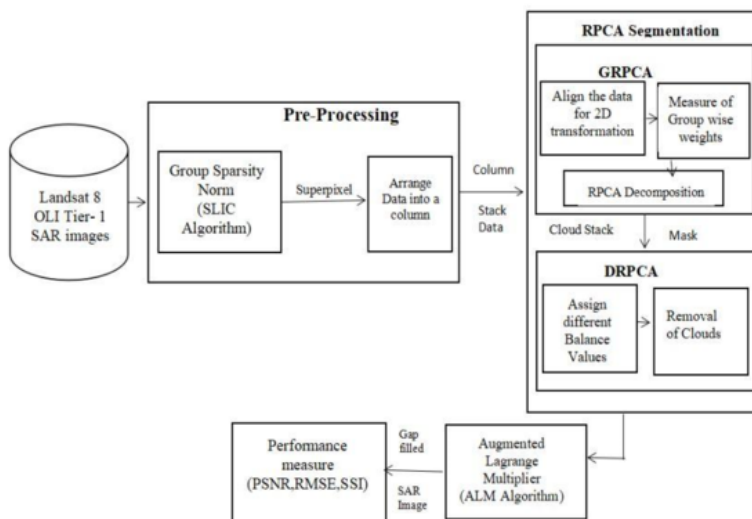
3. EXPERIMENTAL DESIGN

This section discusses the detailed experimental design for the Cloud Removal strategy put forth in this work to address and enhance the Landsat 8 satellite images. Cloud removal in Landsat 8 satellite images, superpixel based segmentation, SLIC algorithm, detection of cloud region, GRPCA algorithm, clouds removal, DRPCA algorithm, filling the missing cloud regions as well as the Image reconstruction algorithm used are discussed in detail.

Cloud Removal in Landsat 8 Satellite Images

Figure 1 explains the input image sequence of the same area obtained at different times can be misaligned. First, simple linear iterative clustering (SLIC) superpixel segmentation and arranging each image to a column of a matrix are conducted as preprocessing. Then, group-sparsity constrained RPCA (GRPCA) combined with geometrical transformation is applied to detect cloud and shadow regions initially and also generate a well aligned image sequence. The dotted box denotes our extension based on group sparsity to align the misaligned image sequence. Finally, discriminative RPCA (DRPCA) is conducted in order to remove clouds and shadows to obtain a sequence of cloud removed images. Finally the satellite image is reconstructed using log det (·) low-rank regularization

Figure 1. Proposed SLIC based Cloud Removal Approach



method. The slope of missing stripes is detected at first by the method of Hough Transform. Missing pixels are then located along the slope using the KNN algorithm to find similar patches within an intercepted local window around the missing point and filled. Thus the clouds are removed to form a gap filled Landsat 8 satellite image.

Super Pixel Based Segmentation

The new superpixel algorithm, Simple linear iterative clustering (SLIC) Radhakrishna Achanta *et.al* (2011) is an adaptation of k-means for superpixel generation, with two important distinctions: 1) the number of distance calculations in the optimization is dramatically reduced by limiting the search space to a region proportional to the superpixel size. This reduces the complexity to be linear in the number of pixels N —and independent of the number of superpixels k . 2) A weighted distance measure combines color and spatial proximity, while simultaneously providing control over the size and compactness of the superpixels. The color image is converted from an RGB color space to a CIELAB color space. A pixels color is represented in the CIELAB color space $[l_i, a_i, b_i]^T$, and $[x_i, y_i]^T$ denotes the feature vector in the XY coordinates. Each pixel has a 5-D feature vector, $C_i = [l_i, a_i, b_i, x_i, y_i]^T$. Image pixels are clustered to generate superpixels using their 5-D feature vector.

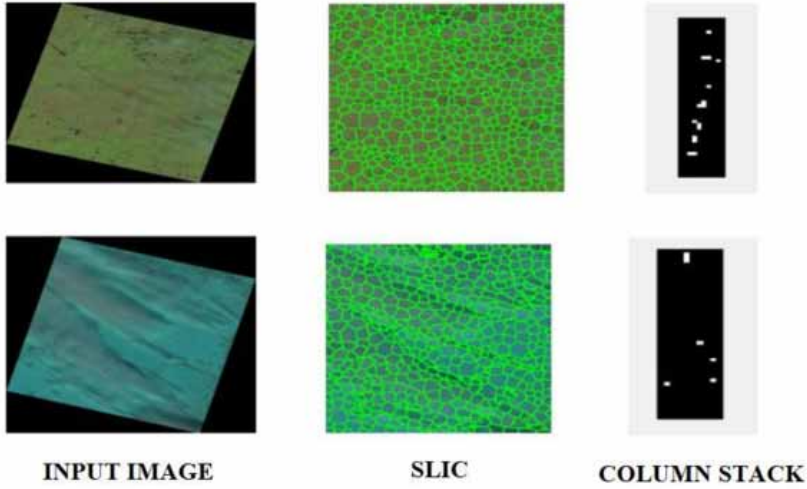
SLIC Algorithm

```
//Initialization
Initialize cluster center  $C_k = [l_k, a_k, b_k, x_k, y_k]$  by sampling
pixels at regular grid steps
Move Cluster Center to the lowest gradient position in a 3x3
neighborhood.
Set label  $l(i) = -1$  for each pixel  $i$ .
Set distance  $d(i) = \infty$  for each pixel  $i$ . //Assignment
for each cluster center  $C_k$  do
for each pixel  $i$  in a  $2S \times 2S$  region around  $C_k$  do
Compute the distance between  $C_k$  and  $i$ .
if  $D < d(i)$  then
Set  $d(i) = D$ 
Set  $l(i) = k$ 
end if
end for
end for
//Update
Compute new Cluster centers
Compute residual error  $E$ .
Until  $E \leq \text{threshold}$ .
```

The straightforward idea to segment pixels into groups is to cluster them into blocks, a new group structure that adapts well to objects in remote sensing images. Each image can be segmented into superpixels. Superpixel technique clusters pixels into perceptually meaningful regions according to their feature similarity explained by Sina Ghassemi *et.al* (2019), such as color, texture, location, and soon, which is flexible to cover random-shaped natural objects. Due to their proper approximation to the boundaries of objects, no further post-processing is required to generate group-sparse outlier regions.

Figure 2 shows that the preprocessed satellite image is transformed in CIELAB color space. First, the cluster centers are initialized. The distance is measured from the cluster center to the data

Figure 2. Output of SLIC



point. If the distance is small then it is merged into the cluster and thus the superpixels are obtained. Thus, the superpixels are made into a column stack.

Detection Of Cloud Region

The Group-sparsity constrained RPCA (GRPCA) proposed by Yongjun Zhanget.al (2019) combined with geometrical transformation is initially applied to detect cloud and shadow regions and also generate a well aligned image sequence. Many other techniques using multi-scale feature convolution neural network proposed by Zhenfeng Shao et.al (2019) and Clouds and Earth's Radiant Energy System proposed by Qing Z. Trepte et.al (2019) (CERES) is used for monitoring clouds and empirical relationship of two landsat-8 visible bands data explained by Haitao Lv et.al (2019) is used for detecting the clouds. The decomposition into three parts, namely, a low-rank part and a group sparse part as usual, and an additional part of noise like sparse outliers modeled by L1-norm.

The GRPCA equation is formulated

$$\min_{L, S, N} \|L\|_* + \lambda \|S\| + \gamma \|N\|_1 \quad (1)$$

$$\text{s.t } D=L+S+N$$

where $\Psi(S)$ is the superpixel group-structured sparsity norm and λ and γ are the positive values controlling the sparsity of group-structured and noise like outliers respectively.

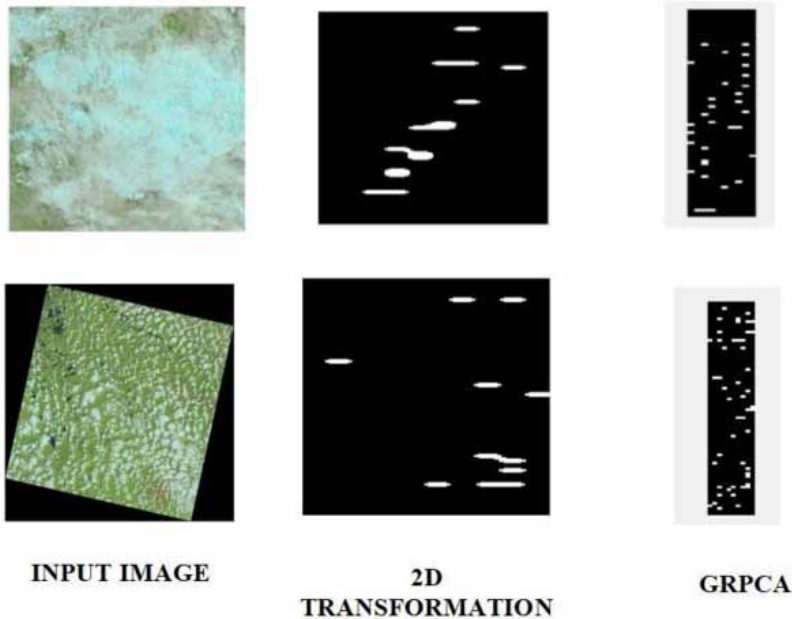
However, the low-rank proposed by X.Liu et.al (2015) is an assumption of background may no longer hold if the images are not well aligned. Due to the complicate acquisition processes, satellite images acquired at different times are always misaligned to some extent. A model for the alignment between satellite images was explained by Y.Peng et.al (2012) as 2-D affine transformation. The groupwise weight value is fairly important in our non-overlapping GRPCA method, especially for the cloud removal task. An intuitive comparison between the cloud pixels and cloud free pixels can be easily made. Based on the RPCA, cloud pixels are decomposed as sparse outliers. By applying a plain RPCA decomposition, the observed matrix is decomposed into a low-rank component and a sparse one.

GRPCA ALGORITHM

- Step1.** Choose the number of clusters (L) and obtain the data points.
Step 2. Place the centroids $L_1, c_2 \dots c_L$ randomly
Step 3. Repeat steps 4 and 5 until convergence or until the end of a fixed number of iterations
Step 4. For each data point x_i :
 - Find the nearest centroid ($c_1, c_2 \dots c_L$)
 - assign the point to that cluster
Step 5. For each cluster $j = 1 \dots L$
 - newcentroid = mean of all points assigned to that cluster
Step 6. End

The figure 3 presents the input images performs 2D transformation. It performs pixel level alignment where similar pixels are been fused together. Thus, they are been arranged into a column stack mask.

Figure 3. Output for GRPCA



Clouds Removal

The low rank component proposed by X.Liu et.al (2015) obtained in the original RPCA is too smooth or blurred for the reason that it is computed by iterative singular value decomposition (SVD) explained by Jiaqing Miao et.al (2019), in order to reduce dimension, and lot of unique information of each column is decomposed into sparse components. If we increase λ to generate a low-rank component with a higher rank to maintain an original cloud free region, then more hosts of cloud and its shadow will be left in the backgrounds indicating ineffective cloud and shadow removal.

The different balance values for cloud as well as shadow pixels and cloud-free pixels guided by the mask, are called DRPCA. Within an over covered cloud mask, a lower balance value would ensure

that all the cloud and its shadow will be entirely decomposed into an outlier matrix and not leave any ghostly presence in the background. For a cloud-free region, the balance value is set to a relatively large value to guarantee background maintenance. The new formulation is defined as

$$\min L, \|L\|_* + \alpha \|P\Omega(S)\|_1 + \beta \|P\Omega - (S)\| \quad (2)$$

$$\text{s.t } \hat{D} = L + S$$

where $\hat{D}$ denotes observed matrix after transformation where

$$\hat{D} = \{vec(I_1 \circ \tau_1), vec(I_2 \circ \tau_2), \dots, vec(I_n \circ \tau_n)\} \quad (3)$$

Ω denotes the cloud and shadow mask obtained, α and β are two discriminative balance values.

The purpose of reconstructing cloud contaminated images, is to recover pixels in cloud and shadow region while maintaining original cloud free pixels at the same time. Therefore, different balance values are assigned for cloud and shadow pixels and cloud free pixels according to the initial region in the first GRPCA step, which is named as DRPCA explained by Yongjun Zhang et.al (2019). Within the cloud-covered region, a lower balance value ensures that all cloud and shadow polluted pixels will be thoroughly decomposed into sparse outlier matrix without leaving any such presence in the background, yet not incurring a large false positive rate.

DRPCA ALGORITHM

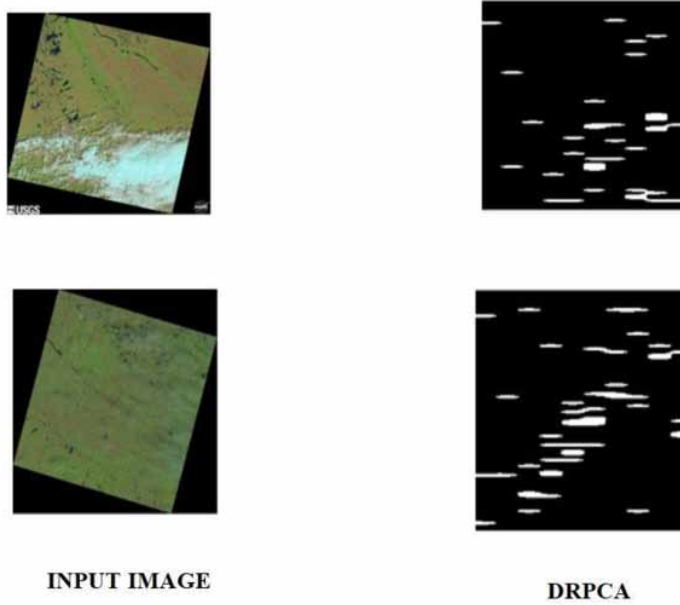
- Step 1: First, randomly select k initial clusters
- Step 2: Randomly assign each data point to any one of the k clusters
- Step 3: Calculate the centers of these clusters
- Step 4: Calculate the minimum intensity value of all the points from the center of each cluster
- Step 5: Depending on this distance, the points are reassigned to the nearest cluster
- Step 6: Calculate the center of the newly formed clusters
- Step 7: Finally, repeat steps (4), (5) and (6) until either the center of the clusters does not change or we reach the set number of iterations.

The Figure 4 shows the input image assigned different balance values for cloud and shadow pixels and cloud-free pixels obtained in the first GRPCA step named DRPCA. Within the cloud-covered region, a lower balance value ensures that all cloud and shadow polluted pixels will be thoroughly decomposed into sparse outlier matrix without leaving any other presence in the background.

Filling The Missing Cloud Regions

Log dot low rank regulation method explained by Jiaqing Miao et.al (2019) method is used for filling the missing region to get the gap filled satellite image. Many techniques namely morphological learning using example based learning proposed by Huihui Song et.al (2018) and information cloning proposed by Chao-Hung Lin et.al (2019) on cloud contaminated patches for multi-temporal satellite images are also conducted. The input is the cloud free SAR images and the output is the gap filled satellite images. The non-convex and non-local low-rank regularization model is used for inpainting the Landsat images. A non-convex regularization model contains a group of self-similar feature patches and a low-rank approximation explained by Fei Wen et.al (2019). The nonlocal self-similarity is to intercept a window in an image, and select an image patch as the sample patch as the window.

Figure 4. Output for DRPCA



The sample patch is compared to other patches in the window to find $m-1$ most similar patches so that there are totally m similar patches in the window. The sample patch and the $m-1$ similar patches are transformed into column vectors and all column vectors are arranged into a matrix, then this matrix will have low rankness. The low rankness of the matrix is very important priori information, which has great significance for the establishment and solution of the inpainting model. The effective part of an image patch is that does not need to be repaired in the patch. A given sample patch should contain no more than 3 data-missing pixels of which the pixel values are set to be zero.

IMAGE RECONSTRUCTION ALGORITHM

- (1) The initial image $\hat{y}$ is estimated using the random valuation method.
- (2) Set the initial parameters: $\lambda, \mu, \tau = \frac{v}{2\mu}$.
- (3) Initialize the weights: $\omega_i = [1, 1, \dots, 1]$ and set $\hat{y}(1) = \hat{y}, \eta(1) = 0$.
- (4) For each sample patch $x_i \setminus \Omega$. Perform merging of patches and find the location M_i of similar patches.
 Loop: for $p=1, 2, \dots, Q$
 Loop for $k=1, 2, \dots, K$
 - (i) Establishment of patch sets $y_i \setminus \Omega$: each sample patch $x_i \setminus \Omega$ and its similar patches form a set of patches.
 - (ii) Inner loop for $L=1, 2, \dots, L$
 - (a) Calculate Z^{l+1}
 - (b) Calculate α^{l+1}
 - (c) $\eta^{l+1} = \eta^l + \beta^l (\alpha^{l+1} - Z^{l+1}). \beta^{l+1} = \rho \beta^l$.

- (d) If $l = L$, then the output $\alpha^l = \alpha^{l+1}$
end for
- (iii) Using formula $\hat{y}^l = D\hat{\alpha}^l$ to calculate $\hat{y}^l$ and used to merge patches and find $y_i \setminus \Omega$
- (iv) Set $Z_i \setminus \Omega = y_i \setminus \Omega$.
- (5) Inner Loop low rank approximation for $J=1,2,\dots,J$
 - (a) If $(K > K_0)$ update weights $\omega_j^k = 1/\alpha_j^k + \varepsilon$.
 - (b) The Singular Value Threshold Value can be calculated $Z_i \setminus \Omega = S\omega_{j,\tau}(y_i \setminus \Omega)$.
 - (c) If $j=J$, then the output $Z_i \setminus \Omega = Z_i \setminus \Omega^j$
end for
 - (6) If $k=K$, the output of the coefficient SR $\hat{\alpha} = \hat{\alpha}^K$
end for
- (7) Using formula $\hat{y} = D\hat{\alpha}$ to calculate $\hat{y}$.
- (8) Using the formula $\frac{\hat{y}}{\Omega} = y / \Omega$ to project the observation data $\frac{y}{\Omega} = \hat{y}$.
end.

The Figure 5 illustrates how the input image which contains the cloud region gaps are filled by the algorithm employed, taking its corresponding color and thus forming a reconstructed image. The Figure 6 illustrates the intermediate results of the input image to form the reconstructed image. First the image undergoes the SLIC and forms a column stack. The alignment of the input image is performed using 2D Transformation and finally the cloud is detected and removed to form the reconstructed image.

Testing is a process of exercising a program with the specific intent of finding errors prior to delivery to the end user to check if the system works accurately and efficiently. The Table 1 summarizes the various possible test samples and the intermediate results obtained along with the result expected.

Figure 5. Output of Gap filled Satellite image

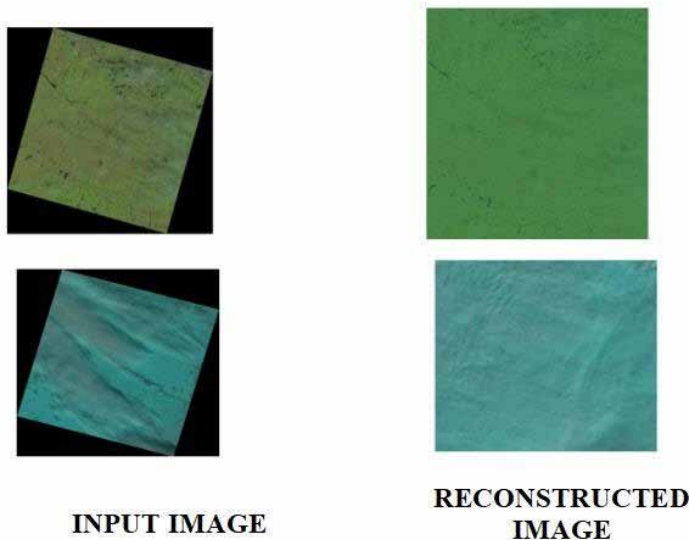
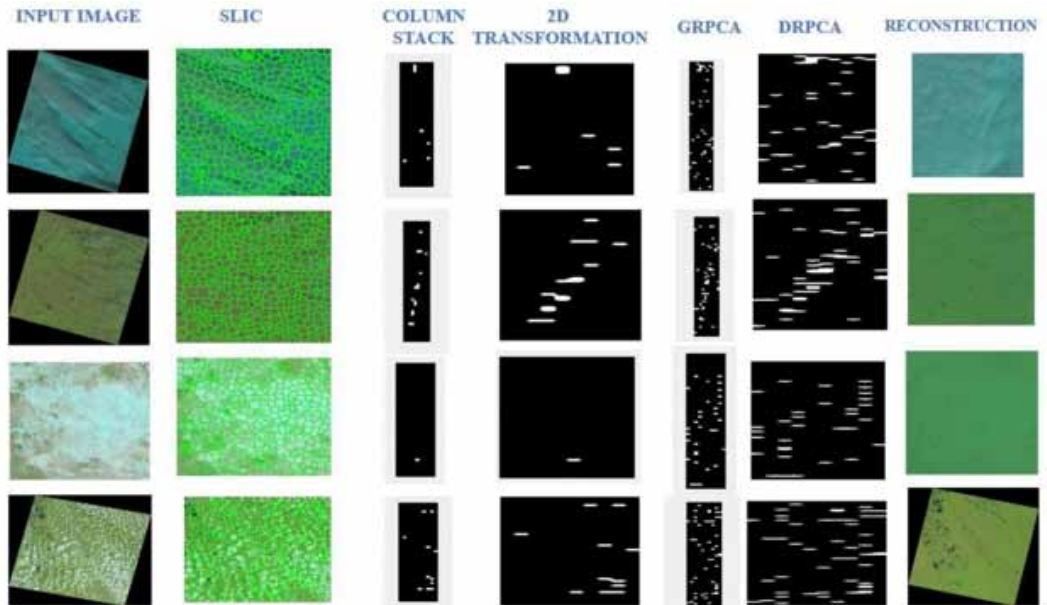


Figure 6. Intermediate results



Module testing carried out are listed in Table 1. DRPCA and GRPCA testing are discussed with both the expected output along with the actual output obtained in the experiments.

4. RESULT ANALYSIS

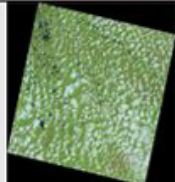
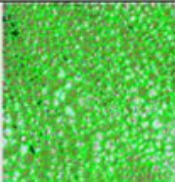
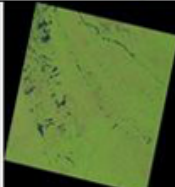
This section presents discussion on the experimental results obtained for the Cloud Removal strategy put forth in this work to address and enhance the Landsat 8 satellite images. Cloud removal in Landsat 8 satellite images, superpixel based segmentation, SLIC algorithm, detection of cloud region, GRPCA algorithm, clouds removal, DRPCA algorithm, filling the missing cloud regions as well as the Image reconstruction algorithm are implemented and the implementation details are given.

The proposed cloud removal framework is implemented using MATLAB R2018a. The dataset contains Landsat 8 Operational Land Imager (OLI) with bands 4, 5, and 6. The images contain 1% to 50% of cloud contamination. It is located in South Dakota, USA which contains ground information. All the Landsat-8 OLI images used in our experiments are Landsat- 8 natural-look products that are compressed and stretched to create an optimization for image selection and visual interpretation. It is a day indicator. The images are collected with Path, 142 and Row Number 52 at USGS. (<https://Landsat.usgs.gov>). The experimental results of the proposed system are analyzed using the evaluation parameters namely, Peak Signal to Noise Ratio (PSNR) and the Root Mean Square Error (RMSE).

Peak Signal to Noise Ratio

PSNR 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. The PSNR is the ratio between a signal's maximum power and the power of the signal's noise. PSNR is used to measure the quality of reconstructed images that have been compressed. Each picture element or pixel has a color value that can change when an image is compressed and then uncompressed. Signals can have a wide dynamic range, so PSNR is usually expressed in decibels, which is a logarithmic scale.

Table 1. Results for various Test Samples

TEST CASE NAME	TEST CASE DESCRIPTION	INPUT	EXPECTED OUTPUT	ACTUAL OUTPUT
1.Group Sparsity Norm	Arrange Data into a Column Stack		Cloud Region is not present which indicated the image is clear	
2.DRPCA	It is used for removing Cloud Region		Removes the Cloud Region and makes the image Clear	Cloud Region removed image
3.Column Stack Data	Places all the Superpixels into a column Stack		Superpixels are Detected	
4.SLIC	It is uses to form a Superpixel			Superpixels are obtained as expected
5.Image Reconstruction	It is used for filling the missing region		Cloud Region is not present which indicates the reconstruction is not required	Image does not require reconstruction
6.SLIC	It is used for Detecting superpixels		Superpixels are not detected on a black image	Superpixels are not detected

Root Mean Squared Error

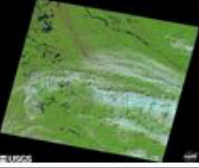
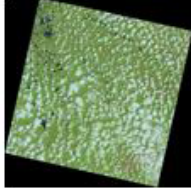
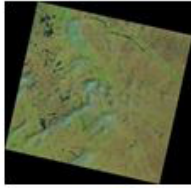
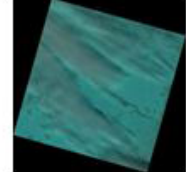
This metric computes the root of the expected squared error between the predicted time values and the ground truth. Among the two monochromatic images, one image is considered to be an approximation of the other. The MSE can be described as the mean of the square of the differences in the pixel values between the corresponding pixels of the two images.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (t_i - \hat{t}_i)^2} \quad (4)$$

$$PSNR = 10\log_{10} \left(\frac{R^2}{MSE} \right) \quad (5)$$

The equations 4 and 5 presents the metrics used to analyze the reconstructed satellite images, the plots for both PSNR and RMSE values are generated. The results are plotted for Red, Green and Blue (RGB) colors. The results show that the PSNR values are high and RMSE values are low. The Table 2 tabulates the values for Landsat 8 reconstructed images and their PSNR and RMSE values. The results show that PSNR values are high and RMSE values are low, which is a good indicator.

Table 2. Values for Landsat 8 reconstructed images

LANDSAT 8 IMAGES	PSNR	RMSE
	R= 36.63 G= 81.80 B= 53.25	R= 0.23 G=4.57 B= 1.32
	R= 38.98 G= 89.08 B= 40.58	R= 0.55 G= 7.93 B= 2.54
	R= 58.96 G= 47.85 B= 38.68	R= 3.56 G= 2.05 B= 1.43
	R= 25.19 G= 35.58 B= 98.45	R= 3.78 G= 4.07 B= 8.46

The Table 3 tabulates the real satellite images and their PSNR and RMSE values. The results are plotted for Red, Green and Blue (RGB) colors. The results show that the PSNR values are low and RMSE values are high.

The figure 7 plots that the graph of PSNR values obtained with various real images and the corresponding reconstructed images. The result shows that the PSNR values are high for reconstructed images compared to real images of Landsat 8 satellite images. Figure 7 shows that all PSNR values of reconstructed Landsat 8 images are above 50 whereas all PSNR values of real Landsat 7 images are lower than 40, which clearly indicates the improvement brought in by the reconstruction of the images. Further on an average, PSNR values of reconstructed Landsat 8 images are above 75, which

Table 3. Values for Landsat 7 real images

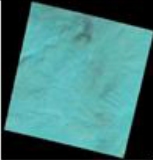
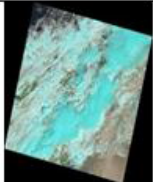
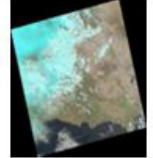
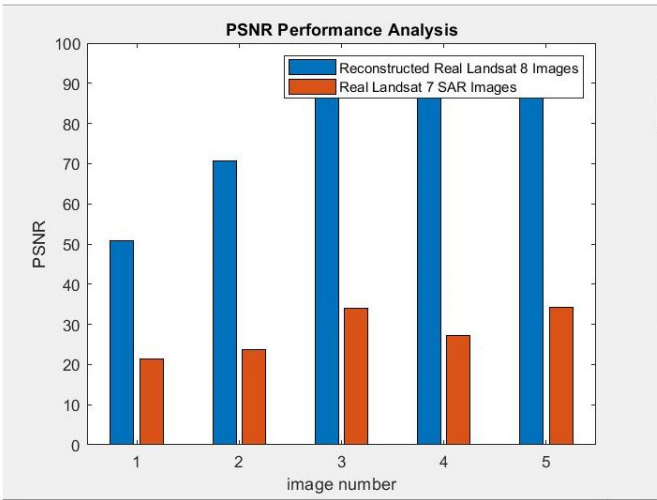
Real Image	PSNR	RMSE
	R=25.74 G=25.733 B=25.730	R=174.64 G=175.04 B=175.16
	R=25.66 G=25.655 B=25.654	R=177.99 G=178.24 B=178.21
	R=25.66 G=25.6598 B=25.6593	R=177.95 G=178.03 B=178.05
	R=25.648 G=25.643 B=25.642	R=178.51 G=178.71 B=178.72

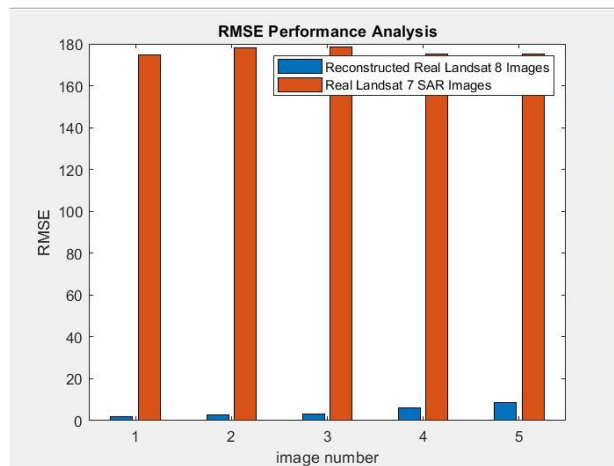
Figure 7. Graph for PSNR values



marks great improvement and paves way for more accurate, relevant information extraction to take up various research initiatives.

The figure 8 plots that the graph of RMSE values obtained with various real images and the corresponding reconstructed images. The result shows that the RMSE values are low for reconstructed images compared to real images of Landsat 8 satellite images. Figure 8 shows that all RMSE values of reconstructed Landsat 8 images are above 170 whereas all RMSE values of real Landsat 7 images are lower than 10, which clearly indicates the improvement brought in by the reconstruction of the images. Further on an average, RMSE values of reconstructed Landsat 8 images are above 175, which marks great improvement and paves way for more accurate, relevant information extraction to take up various research initiatives from these Landsat 7, 8 images available publicly.

Figure 8. Graph for RMSE Values



5. CONCLUSION

Clouds present in the satellite images degrade the observations that can be made. Thus the removal of the clouds is of a great importance. The method proposed in this work takes spatial coherence into consideration and adopts superpixels to cluster object pixels. Group sparsity constrained RPCA is proposed to detect initial cloud region. Specifically, we apply non-overlapping groups and design group wise weights to facilitate segmentation between cloud and cloud-free groups. The removal of the clouds is performed using DRPCA. The values for PSNR are varying from 25 in Landsat 7 real images to 90 in Landsat 8 reconstructed real images in Green channel and RMSE has changed from 175 in Landsat 7 real images to 3 in Landsat 8 reconstructed real images in Red channel. This indicates that Landsat 8 reconstructed real images have greater quality and error rate in less. The limitation in this work is we have compared reconstructed real images with Landsat 7 real images, experiments can be conducted for wider experimental analysis for more generalized inferences. In the future, based on 2-D transformation, it is worth extending the method to process images from different optical sensors with similar resolution.

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