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CLOUD REMOVAL IN LAND SAT 8SAR IMAGES

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Abstract: **The Landsat 8 Operational Land Imager (OLI) provides a valuable data source for land surface mapping and monitoring. 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 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. This proposed concept is formulated using Simple Linear Iterative Clustering(SLIC) for clustering the similar super pixels and forming a Column Stack and Group Sparsity Constrained Robust principal component Analysis(GRPCA) is used to detect cloud initially by assigning groupwise weights and also generate a column stack mask and Discriminative Robust Principal Component Analysis(DRPCA) is conducted to remove clouds to obtain a cloud free SAR images. Finally the impainting is performed by finding the similar patches using the log det(.) low rank regulation method to obtain the Gap filled Satellite images. The result are compared using the Landsat 8 Real Images and the Landsat 8 reconstructed satellite image using Peak Signal-to- Noise Ratio (PSNR), Root Mean Square Error(RMSE) are used to evaluate their reconstruction accuracy.**

Keywords- **Landsat 8 Enhanced Thematic Mapper Plus, Group Sparsity Constrained Principal Component Analysis, Discriminative Robust Principal Component Analysis, Impainting Algorithm**
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I. 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 [1] 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 ground cover information being observed, thus solutions are required urgently to overcome such a challenging problem.

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.

Since the algorithm is applied to the entire study area, we need not only to assess the algorithm's ability to remove clouds. S. Qiu et.al [23] 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. With the policy of free and open Landsat data, some automated cloud detection methods were developed based on multitemporal Landsat images and can achieve better results. For cloud shadow detection, the geometry-based approach is widely used in the single date algorithms. Meanwhile, by using multitemporal Landsat images, some researchers used the image differencing method to better identify cloud shadow.

Fei Wen et.al[24] Due to the inevitable existence of clouds and their shadows in optical remote sensing images, certain ground-cover information is degraded . A proposed a two-pass robust principal component analysis (RPCA) framework for cloud removal in the satellite image sequence. 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 proposed concept is formulated using Simple Linear Iterative Clustering(SLIC) for clustering the similar superpixels [2] and form a Column Stack. The cloud detection and removing [5] 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 [1] is applied to detect cloud and shadow regions initially and also generate a well aligned image sequence. A 2-D Transformation [4] is performed on the satellite images to get a well aligned satellite images. Finally, Discriminative RPCA (DRPCA) is conducted to remove clouds and shadows [1] to obtain a sequence of cloud removed images. The reconstruction is carried out using log det (·) low-rank regularization method [6]. 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 results show the capability to remove cloud.

II. LITERATURE SURVEY

Radhakrishna Achanta et.al [2] 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. A new superpixel algorithm, simple linear iterative clustering (SLIC), which adapts a k-means clustering approach to efficiently generate superpixels.

Liang Yan et.al [11] 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.To solve this problem, many adversarial-based domain adaptation methods have been proposed.

Xiangchao Meng et.al [12] explains about the optical remote sensing images not only . In this paper, a pansharpening method for the challenging cloud- contaminated very high-resolution remote sensing images is proposed. In the proposed methods, a two- step fusion framework based on multisource and multitemporal observations is presented: 1) the thin clouds, the haze, and the light cloud shadows are proposed to be first jointly removed and 2) a variational-based integrated fusion model is then proposed to achieve the joint resolution enhancement and missing information reconstruction for the thick clouds and dark cloud shadows.

Yongjun Zhang et.al [1] proposed a method for Clouds and accompanying shadows, The cloud contamination problems with the objective of generating cloud-removed remote sensing images. 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 accompanying shadows), and noise respectively.

In summary, 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 a sequence.

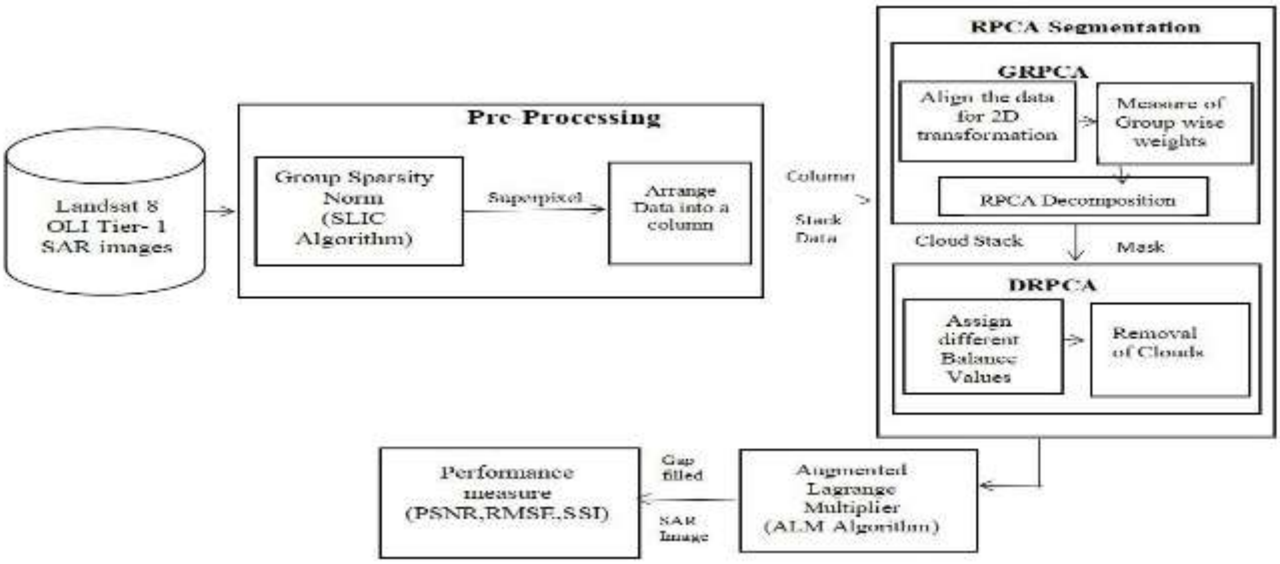

Figure3.1. BlockDiagram

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Figure 3.1 explains about the 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) 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 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 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.

SUPERPIXEL BASED SEGMENTATION

Radhakrishna Achanta proposed that a new superpixel algorithm, Simple linear iterative clustering (SLIC)[2] 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 [li , ai , bi]T, and [xi , yi]T denotes the feature vector in the XY coordinates. Each pixel has a 5-D feature vector, Ci = [li , ai , bi , xi , yi]T . Image pixels are clustered to generate superpixels using their 5-D feature vector.

BASIC ALGORITHM OF SLIC

1: Initialize cluster centers $C_k = [l_k, a_k, b_k, x_k, y_k]^T$ by sampling pixels at regular grid steps S.
2: Perturb cluster centers in an $n \times n$ neighborhood, to the lowest gradient position.
3: **repeat**
4: **for** each cluster center C_k **do**
5: Assign the best matching pixels from a $2S \times 2S$ square neighborhood around the cluster center according to the distance measure (Eq. 1).
6: **end for**
7: Compute new cluster centers and residual error E $\{L1$ distance between previous centers and recomputed centers$\}$
8: **until** $E \leq$ threshold
9: Enforce connectivity.

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 [9], such as color, texture, location, and so on, which is flexible to cover random- shaped natural objects. Due to their proper approximation to the boundaries of objects, no further postprocessing is required to generate group-sparse outlier regions.

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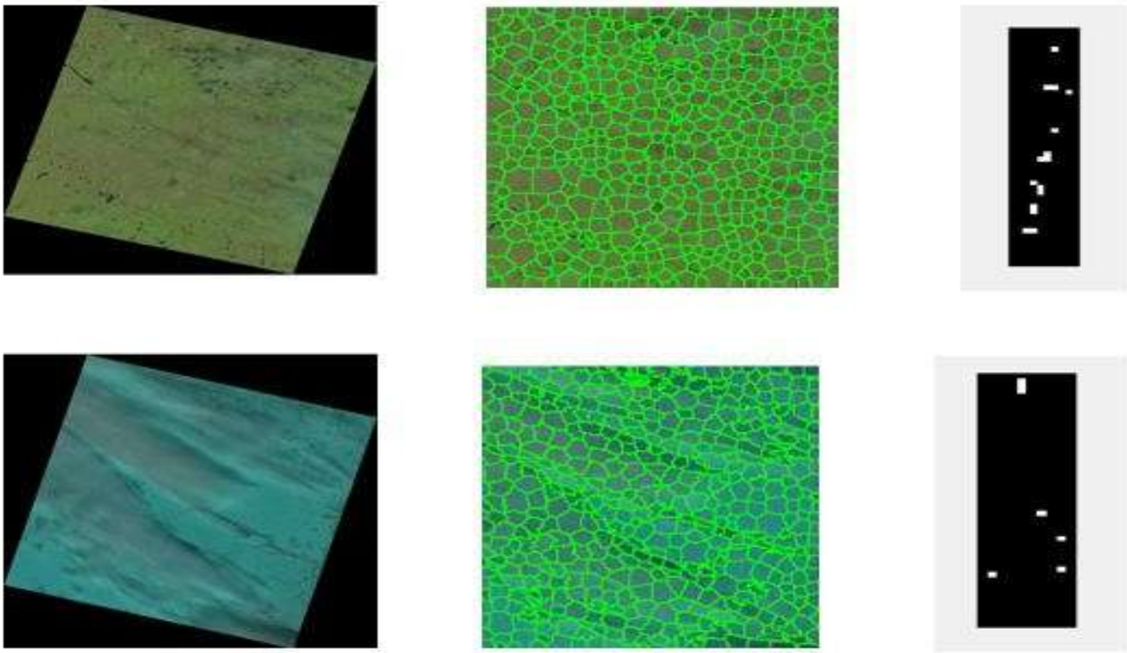

INPUT IMAGE **SLIC** **COLUMN STACK**

Figure4.1. Output ofSLIC

Figure 4.1 explains 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 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)[1] combined with geometrical transformation is applied to detect cloud and shadow regions initially and also generate a well aligned image sequence. Many other techniques using multiscale feature convolution neural network [19] and Clouds and Earth's Radiant Energy System [20] (CERES) is used for monitoring clouds and empirical relationship of two landsat-8 visible band data[21] 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.

However, the low-rank [3] 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 as 2-D affine transformation[4]. The groupwise weight value is fairly important in our no overlapping GRPCA method, especially for the cloud removal task. An intuitive comparison between the cloud pixels and cloud-free pixels can be made easily.

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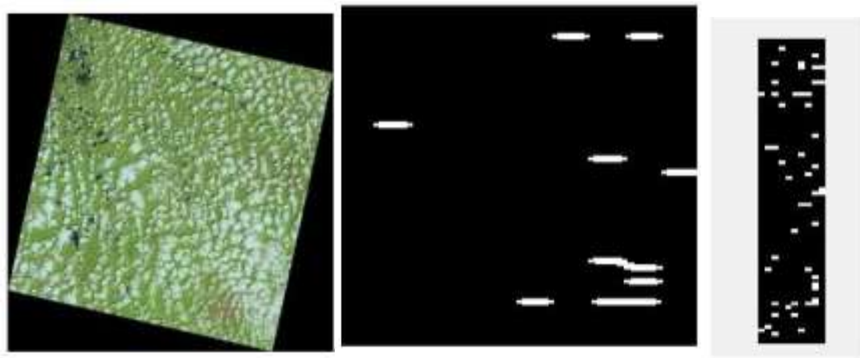


INPUT IMAGE 2DTRANSFORMATION GRPCA

Figure4.2. OutputforGRPCA

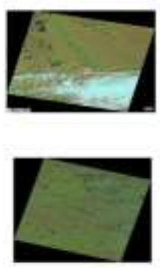
The figure 4.2 describes the input images performs 2D Transformation. It performs Pixels Level Alignment where similar pixels are been fused together. Thus they are been arranged into a column stack mask.

REMOVAL OF CLOUDS

The low rank component [3] obtained in the original RPCA is too smooth (or blurred) for the reason that it is computed by iterative singular value decomposition (SVD) [6] to reduce dimension, and a 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 ghosts of cloud and its shadow will be left in the backgrounds indicating ineffective cloud and shadow removal.

A different balance values for cloud and shadow pixels and cloud-free pixels guided by the mask, which we call it the 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, balance value is set to a relatively large value to guarantee background maintenance.

The purpose of reconstructing cloud contaminated images, we hope to recover pixels in cloud and shadow region while maintaining original cloud free pixels at the same time. Therefore, we assign different balance values for cloud and shadow pixels and cloud- free pixels according to the initial region obtained in the first GRPCA step[8], which we name it as DRPCA[1].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 ghostly presence in the background, yet not incurring a large false positive rate.



INPUT IMAGE

DRPCA

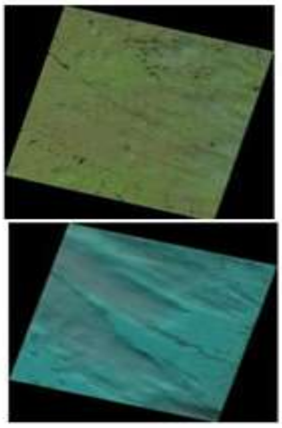
FILLING THE MISSING CLOUD REGIONS

Log dot low rank regulation method [6] method is used for filling the missing region to get the gap filled satellite image. Many techniques like using Morphological learning using example based learning [17] and information cloning [18] on cloud contaminated patches for multitemporal satellite images are also conducted.

The input is the Cloud Free SAR images and the output is the Gap filled Satellite images. The no convex and nonlocal low-rank regularization model for in painting the Landsat images. A no convex regularization model contains a group of self-similar feature patches and a low- rank approximation [1] . The nonlocal self-similarity is to intercept a window in an image, and select an image patch as the sample patch as the window.

The sample patch is compared to other patches in the window to find, say, 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.

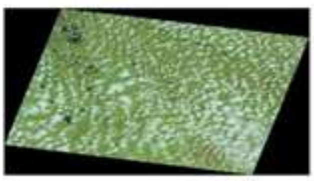
The low rankness of the matrix is very important priori information, which has great significance for the establishment and solution of the in painting model. The effective part of an image patch is that does not need to be repaired in the patch. A given sample patch should contain no more than 3 data-missing pixels of which the pixel values are set to be zero.



INPUT IMAGE

RECONSTRUCTED IMAGE

III. RESULTS

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 Performance of the proposed system is based on the Peak Signal to Noise Ratioand the Root Mean Square Error.

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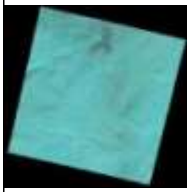
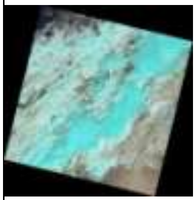
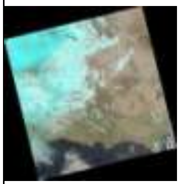
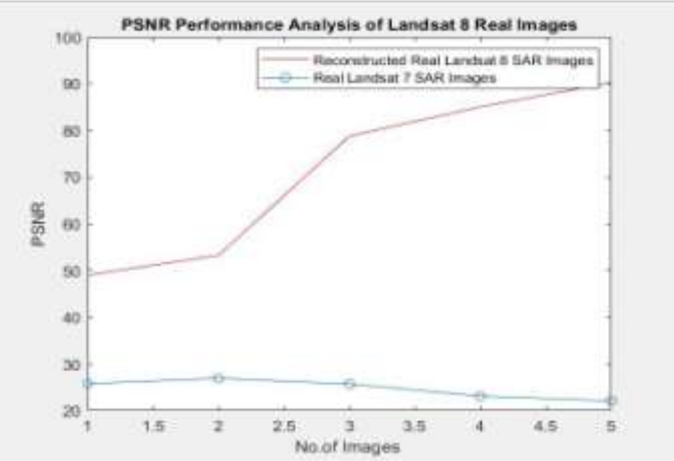
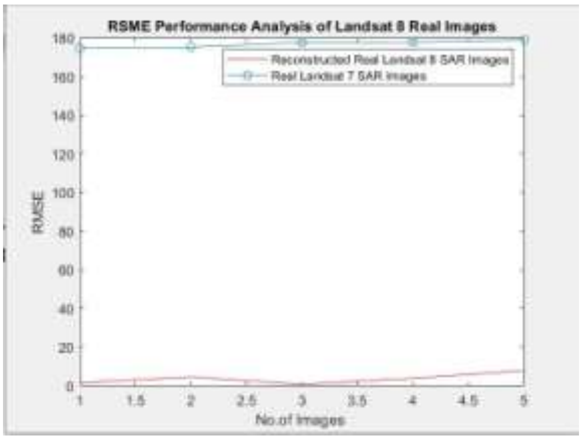
Table5.4. ValuesforLandsat7 RealImages

RealImage	**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



The Figure describes the graph is plotted between images taken with the PSNR values. The results shows that the PSNR Values are high for Reconstructed Images compared to Real images of Landsat 8 Satellite images.



The graph is plotted between images taken with the RMSE values. The result shows that the RMSE values are low for Reconstructed images compared to Real Images of Landsat 8 SAR images.

IV. CONCLUSION

Clouds present in the satellite image degrades the earth observation. Thus the removal of the clouds is of a great importance. The method 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 no overlapping groups and design groupwise weights to facilitate segmentation between cloud and cloud-free groups. The removal of the clouds is performed using Discriminative Robust Principal Component Analysis. Finally the missing gaps are filled using Augmented Lagrange Multiplier. Experiments are been carried out by comparing Landsat 7 Cloud present Real images with Landsat 8 Cloud Removal real images shows that Peak signal to Noise Ratio is High and Root Mean Square Error is less. In the future, based on 2-D transformation, it is worth extending the method to process images from different optical sensors with similar resolution.

V. REFERENCES

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