Remotely Sensed Image Inpainting With MNLTV Model

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Abstract—Image processing is an significant component of modern technologies as it provides the perfection in pictorial information for human interpretation and processing of image data for storage, transmission and representation. In remotely sensed images because of poor atmospheric condition and sensor malfunction (Instrument error such as SLC-OFF failure on may13,2003 the scan line corrector (SLC) of LANDSAT7 Enhanced Thematic Mapper Plus (ETM+) sensor failed permanently causing around 20% of pixel not scanned which become called dead pixels) there is usually great deal of missing information which reduce utilization rate. Remotely sensed images often suffer from strip noise, random dead pixels. The techniques to recover good image from contaminated one are called image destriping for strips and image inpainting for dead pixels, therefore reconstruction of filling dead pixels and removing uninteresting object is an important issue in remotely sensed images. In past decades, missing information reconstruction of remote sensing data has become an active research field and large number of algorithms have been developed. This paper presented to solve image destriping, image inpainting and removal of uninteresting object based on multichannel nonlocal total variation. In this algorithm nonlocal method considered, which has superior performance in dealing with textured images. To optimize variation model a Bregmanized-operator-splitting algorithm is employed. Furthermore proposed inpainting algorithm is used for text removal, scratch removal, pepper and salt noise removal, object removal etc. The proposed inpainting algorithm was tested on simulated data.

Keywords- *Image Inpainting, Multichannel, Nonlocal Total Variation , Remotely Sensed Images ,Landsat7 SLC-off reconstruction .*

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I. INTRODUCTION

Remote sensing instruments can capture information about the atmosphere, ocean, and the Earth's surface. They are one of the most frequently used and most powerful approaches to understanding and investigating our planet. However, in some situations, such as detector failure or image damage, dead pixels will exist in the remotely sensed images. Dead pixels are those pixels whose measurement does not have any correlation with the true scene that is being measured [1]. The existence of dead pixels severely degrades the quality of the imagery so that the data usability is greatly reduced.

For example, 15 of the 20 detectors in the Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) band 6 are ineffective [2]; the scan line corrector (SLC) of the Landsat enhanced thematic mapper plus (ETM+) sensor has permanently failed [3]. Dead pixels resulting from sensor failure or random dead pixels are also a common observable fact. There are also some situations in which we need to remove or replace certain objects from the imagery for the sake of improving its application value. For example, we can remove the map lettering and labels on a raster image map to obtain the original image data and remove pedestrians on a zebra crossing to reconstruct the zebra crossing on an aerial image. The recovery of dead pixels and the removal of selected objects from remotely sensed images can be unified into one problem, i.e., image inpainting, which has been intensively studied in the field of digital image processing. The objective of image inpainting is to reconstitute the missing or damaged portions of image, in order to make it more legible and to restore its unity.

II. RELATED WORK

To solve the inpainting problem of remotely sensed images, various algorithms for reconstructing the dead pixels of remote sensing data are divided into three main classes, According to the different sources of the complementary information when reconstructing the dead pixels, algorithms can be primarily classified into three categories [4].

a) Temporal-based methods, which extract the complementary information from other data acquired at the same position and at different time periods.

-Multi Source Method

b) Spectral-based methods, which extract the complementary information from other spectra.

-Multi Source Method

c) Spatial-based methods, without any other auxiliary information source.

- Single Source Method

The first category consist of Multitemporal-complementation-based approaches, which extract the complementary information from other data acquired at same position and different time periods. Examples of these approaches are described in the works in [5] and [6], in order to fill the Landsat-7 scan line corrector-off (SLC-off) gaps, the authors use the data from multiple Enhanced Thematic Mapper Plus (ETM+) scenes to provide complete ground coverage.

The second category comprises the Multispectral complementation-based approaches, which extracts the complementary information from another spectra specifically clear and complete band of data to recover the contaminated band of data by modeling a relationship between the contaminated band and the reference band. Example of this approach is described in [7] describes how to restore the missing data of Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) band 6 by the use of other correlated bands, such as the commonly used Aqua MODIS band 7, or other image data.

Both categories of approaches mentioned earlier need complementary information from other acquired images or spectral bands. However, in many cases, complementary images or bands cannot be acquired. Therefore, a third category of approaches is explored, Spatial based approach, which consists of filling in the missing data regions using the remaining parts in the image. Example of this approach is the research work in [8] describes how to synthesize the missing regions in remotely sensed images by propagating the geometrical structure from the remaining parts around the missing zone. The goal of the approaches in this category is to seamlessly synthesize a complete, visually plausible, and coherent image. Since there is no need for auxiliary data, the third strategy of approaches is more attractive. Most prior researchers in this category have only made use of the local neighboring information to reconstruct the missing regions in remotely sensed images, which is far from sufficient. To remove these weaknesses, this paper presents an efficient proposed algorithm for missing data synthesis. The proposed algorithm unites the advantages of nonlocal methods, which have a superior performance when dealing with textured images and local methods, which are good at recovering geometric structures such as image edges. Furthermore, it takes advantage of the multichannel data of remotely sensed images to achieve spectral coherence for the reconstruction result. That is to say, proposed method can achieve both the spatial and the spectral coherence. In order to optimize the proposed multichannel nonlocal total variation inpainting model, a Bregmanized Operator Splitting (BOS) algorithm is employed.

III. PROPOSED SYSTEM

This section describes proposed technique for Remotely sensed image inpainting with MNLTV model.

A. BASIC INPAINTING MODEL

a) Image Observation Model

First, assuming that a multispectral image with some pixels missing, the degradation model can be written as

$$f = Au + \varepsilon \tag{1}$$

where $u = [u1, u2, \dots, u_B]$ is the original true image, with the size of $M \times N \times B$, in which M represents the samples of the image, N stands for the lines of the image, and B is the number of bands. $f = [f1, f2, \dots, f_B]$ is the observed degradation image, which is also of size $M \times N \times B$. A is a diagonal matrix with diagonal elements consisting of 0 and 1, with 0 representing the missing data. ε is additive noise with the same size as u and f. Our objective is to find the unknown target image u from the observed image f.

b) Image Inpainting Model

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The multispectral image inpainting process is essentially an ill-posed inverse problem, which is similar to many other image processing problems, such as image denoising, destriping, superresolution reconstruction and others. The work provided in [9] and [10] approaches that achieve superresolution reconstruction and inpainting simultaneously. It is standard to use a regularization technique to make these inverse problems well posed. Regularization methods assume some prior information about the unknown image u, such as smoothness, sparsity, manifold, or small TV. Based on a regularization technique, the inpainting problem for a multispectral image can be represented by the following model:

$$\hat{u} = \arg\min_{u} J(u) \quad \text{s.t. } Au = f \tag{2}$$

where $J(u)$ is the regularization item giving a prior model of the target image. The corresponding constrained problem for a noisy case is then written as

$$\hat{u} = \arg\min_{u} J(u) \quad \text{s.t } \|Au - f\|^2 \le \sigma \tag{3}$$

where σ is the standard deviation of the noise ε.

B. MNLTV METHOD

Almost all the regularization methods mentioned earlier are belongs to local methods which recover pixel by using local neighbouring information, it is not sufficient hence nowadays nonlocal methods for image denoising and inpainting have gained more attention due to their superior performance in dealing with texture images. Local methods have proved very effective for recovery of Geometric structure such as image edges. Synthesis of both types of method is an important research area. Variation analysis is an appropriate tool for unification of local and nonlocal methods. In order to take advantage of multichannel data of remotely sensed images, an MNLTV inpainting model is presented here. Figure1 shows diagrammatic illustration of the proposed approach. The work explicitly focuses on Multichannel Nonlocal Total Variation with Split Bregman method.

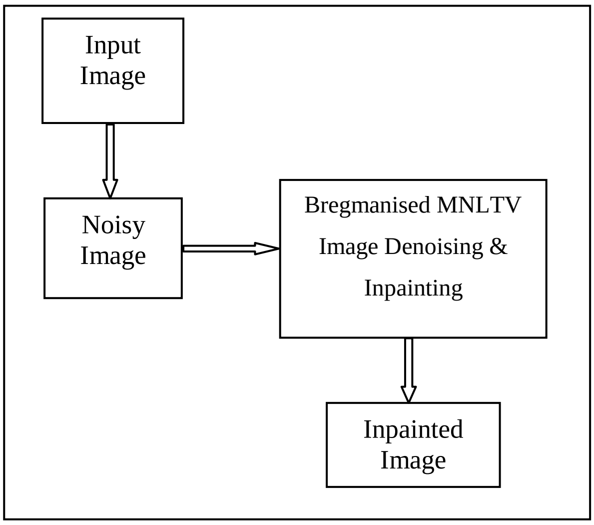

Figure 1: Diagrammatic Illustration of the Proposed Approach.

a) Nonlocal Filter

The nonlocal means algorithm was first formulated in 2005 by Buades etal. in [11] and has found immense application in wide area of research covering medical images to satellite images. It is generalization of neighbourhood filter originally developed by Yaroslavsky in 1985 and patch based methods. The idea is to restore an unknown pixel by using other similar pixel. That is any point can directly interact with any other point in image domain and hence the name nonlocal. The resemblance is regarded in terms of patch centered at each pixel, not just intensity of pixel itself. In order to restore pixel, the nonlocal method average the other pixel with structures or patches similar to that of the current one. More precisely, given a reference image f, Ω is its pixel domain. Here define the NL means solution NLM_u of the image u at point x as

$$NLM_u(x) := \frac{1}{C(x)} \sum_{y\in\Omega} w_f(x,y) f(y) \quad (4)$$

where

$$w_f(x,y) = \exp\{-\frac{G_a^* \left| f(x+.) - f(y+.) \right|^2 (0)}{h^2}\} \quad (5)$$

$$C(x) = \sum_{y\in\Omega} w_f(x,y) \quad (6)$$

where G_a is the Gaussian kernel with standard deviation a, $C(x)$ is the normalizing factor, h is filtering parameter, and $f(x + \cdot)$ can be known as a patch centered at a point x. The patch $f(x + \cdot)$ of size $m \times m$ (m is chosen as an odd number) is given , and the size of the patch is according to the noise intensity

$$(\frac{G_a^* \left| f(x+.) - f(y+.) \right|^2}{h^2})(0) = \sum G_a(t) \left| f(x+t) - f(y+t) \right|^2 \quad (7)$$

Following above equation(5) can compute a weight function $w_f(x,y)$ between two points x and y by using the difference of patches around each point. This choice of weight is very efficient in reducing noise while preserving the textures and contrast of natural images.

b) Nonlocal Operators

In order to formulate the NL-means filter in a variational framework, Gilboa and Osher defined variational framework-based nonlocal operators. Definitions of the nonlocal functions introduced in [12] is given below. The Nonlocal Total Variational framework algorithmic makes it altogether a non linear approach. The Total Variation based techniques is broadly used in inverse problems like denoising, inpainting etc which gives out excellent results.

The main principle behind Total Variation denoising is the signals with spurious details will have high total variance and hence the gradient of the image will also be high. In a way to preserve the edge details and recreating an estimate of the original image iteratively, it does a minimization approach of the total variance. The benefit of the combination of the two techniques appears to be that the method manages to capture the best features, the patch redundancy in NL means and the nice denoising of edges in TV [13].

Let $\Omega \subset R^2$, $x, y \in \Omega$, $u(x)$ be a real function $u : \Omega \to R$, and $w_f(x,y)$ be a weight function. Furthermore, $w_f(x,y)$ is assumed to be nonnegative and symmetric. Nonlocal gradient $\nabla_w u(x) : \Omega \to \Omega \times \Omega$ is defined as the vector of all partial derivatives $\nabla_w u(x,\cdot)$ at x such that

$$(\nabla_w u)(x,y) := (u(y) - u(x)\sqrt{w(x,y)} \;\; \forall y \in \Omega \quad (8)$$

vectors are denoted as $\vec{p} = p(x,y) \in \Omega \times \Omega$, and the nonlocal divergence $(div_w \vec{p})(x) := \Omega \times \Omega \to \Omega$ is defined as the adjoint of the nonlocal gradient

$$(div_w \vec{p})(x) := \sum_{y\in\Omega} (p(x,y) - p(y,x))\sqrt{w(x,y)} \quad (9)$$

The nonlocal NLTV is defined as follows

$$J_{NLTV}^{w}(u) := \sum_{x\in\Omega} \left| \nabla_w u(x) \right| = \sum_{x\in\Omega} \times \sqrt{\sum_{y\in\Omega} (u(x) - u(y))^2 w(x,y)} \quad (10)$$

c) MNLTV

For multichannel images, Blomgren and Chan[14] presented a multichannel TV (MTV) regularization by coupling the channels

$$J_{MTV}(u) := \sum_{x\in M\times N} \sqrt{\sum_{j=1}^{B} \left| \nabla u_j(x) \right|^2} \quad (11)$$

The work of Yuan et al. [15] demonstrated that this MTV model has a powerful spectrally adaptive ability in remotely sensed image processing. Inspired by the previously mentioned work, here proposed an MNLTV regularization for multispectral images.

$$J_{MNLTV}^{w}(u) := \sum_{x\in M\times N} \sqrt{\sum_{j=1}^{B} \left| \nabla_w u_j(x) \right|^2}$$

$$= \sum_{x\in M\times N} \sqrt{\sum_{j=1}^{B} \sum_{M\times N} (u_j(x) - u_j(y))^2 w(x,y)} \quad (12)$$

d) MNLTV Inpainting Models

According to the inpainting models mentioned in equations (2) and (3) the corresponding MNLTV inpainting model is

$$\hat{u} = \arg\min_u J_{MNLTV}^{w}(u), \quad \text{s.t. } Au = f \quad (13)$$

In a noisy case, the model is then written as

$$\hat{u} = \arg\min_u J_{MNLTV}^{w}(u), \quad \text{s.t. } \left\| Au - f \right\|^2 \le \sigma \quad (14)$$

C. OPTIMIZATION

Based on a Bregman method, a well-performing optimization algorithm called BOS [16] was developed to provide a general algorithm framework for equality-constrained convex optimization. In this paper, the BOS algorithm is extended and used to optimize the MNLTV inpainting model. The basic idea of this optimization algorithm can be stated as follows. First, the constraint problems in (13) and (14) are enforced with the Bregman iteration process

$$\begin{cases} u^{k+1} = \arg\min_u (\mu J_{MNLTV}^{W}(u) + \frac{1}{2}\left\| Au - f \right\|^2) \\ f^{k+1} = f^k + f - Au^{k+1} \end{cases} \quad (15)$$

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where μ is a positive parameter $\mu > 0$; it is the regularization term scale. The first sub problems can sometimes be difficult and slow to solve directly since it involves the inverse of the operator A and the convex function J^{w}_{MNLTV} in (13). The forward–backward operator splitting technique is used to solve the unconstrained sub problem in (15) as follows: For $i \geq 0$, $u^{k+1,0} = u^{k}$

$$\begin{cases} v^{k+1,i+1} = u^{k,i} - \delta A(u^{k+1,i} - f^{k}) \\ u^{k+1,i+1} = \arg\min_{u} \times (\mu J^{w}{MNLTV}(u) + \frac{1}{2\delta}\left\|u - v^{k+1,i+1}\right\|^{2}) \end{cases} \quad (16)$$

where δ is a positive parameter such that $0 < \delta < (2 / \|A\|)$.It shows the efficiency of the BOS algorithm depends on solvers for the u sub problem in (16). Here split Bregman method in [17] is extended to the multichannel nonlocal case. It has proved to be a fast and efficient algorithm to minimize the MNLTV function in the sub problem

$$\hat{u} = \arg\min_{u}(\mu\delta J^{w}_{MNLTV}(u) + \frac{1}{2}\|u - v\|^{2}) \quad (17)$$

The idea is to reformulate the problem as

$$\hat{u} = \min_{u}(\mu\delta \sum_{x \in M \times N} \sqrt{\sum_{j=1}^{B} d_{j}(x)^{2}} + \frac{1}{2}\|u - v\|^{2}) \quad (18)$$

$$s.t.\, d_{j} = \nabla_{w} u_{j}$$

By enforcing the constraint problem with a Bregman iteration process, the extended MNLTV split Bregman algorithm using the MNLTV norm is given by

$$\begin{cases} (u^{k+1}, d^{k+1}) = \min_{u}(\mu\delta \Sigma_{x \in M \times N} \sqrt{\Sigma_{j=1}^{B} d_{j}(x)^{2}} \\ + \frac{1}{2}\|u - v\|^{2} + \frac{\lambda}{2}\left\|d - \nabla_{w} u - b^{k}\right\|^{2} \\ b^{k+1} = b^{k} + \nabla_{w} u^{k+1} - d^{k+1} \end{cases} \quad (19)$$

where λ is the scale of penalty term $\left\|d - \nabla_{w} u - b^{k}\right\|^{2}$ it is usually inversely proportional to the value of $\mu \cdot \delta$. The solution of (19) is obtained by performing alternately with the following two sub problems:

$$\begin{cases} u^{k+1} = \min_{u}(\frac{1}{2}\|u - v\|^{2} + \frac{\lambda}{2}\left\|d^{k} - \nabla_{w} u\right\| - b^{k}) \\ d^{k+1} = \min_{d}(\mu\delta \Sigma_{x \in M \times N} \sqrt{\Sigma_{j=1}^{B} d_{j}(x)^{2}} \\ + \frac{\lambda}{2}\left\|d - \nabla_{w} u^{k+1} - b^{k}\right\|^{2} \end{cases} \quad (20)$$

The subproblem for u^{k+1} consists of solving the linear system

$$(u^{k+1} - v) - \lambda div_{w}(\nabla_{w} u^{k+1} + b^{k} - d^{k}) = 0 \quad (21)$$

As the linear function in (21) is strictly diagonal, u^{k+1} can be solved by a Gauss–Seidel algorithm.

The d^{k+1} subproblem equation in (20) can be solved using a shrinkage operator as follows:

$$d^{k+1} = shrink(\sqrt{\sum_{j=1}^{B} (\nabla_{w} u_{j}^{k+1} + b^{k})^{2}}, \frac{\mu\delta}{\lambda}) \quad (22)$$

$$\text{Where} \quad shrink(x, \tau) = \frac{x}{|x|}\max(|x| - \tau, 0) \quad (23)$$

The optimization procedure of the MNLTV inpainting model is described in Algorithm 1.

```
Initialize: u_0 = u, d = 0, b = 0
    while ||u^{k+1} - u^k|| ≥ tolerance
    solve the subproblem of u
    solve the subproblem of d
    update Bregman variable b
end
```

Algorithm 1.

IV. RESULTS

In the simulation experiments six experiments are tested and verified the efficacy of proposed inpainting algorithm and the improvement in speed. Results of the six experiments are shown in Figures 2 to 15. Here some tests are performed on several images ranging from simple images to the images with complex textures and compared the obtained results with the existing approaches. Some of the images that present here are taken from the previous literature and cite the appropriate paper wherever possible. Results of six experiments are shown in figure 2 to figure 15 verify the efficiency of proposed MNLTV inpainting algorithm with respect to PSNR ,SSIM, metric Q (MQ) are shown in TABLE 1.

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Figure 2 : Original Image [4].

Figure 3 : Noise contaminated Image and Noise Removal Image by Proposed Algorithm.

Figure 4 : Original Image.

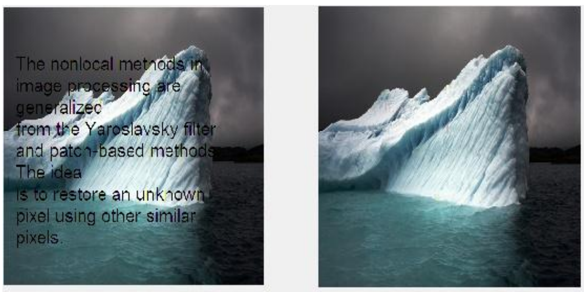

Figure 5 : Overlaid Text contaminated Image and Text Removal Image by Proposed Algorithm.

Figure 6 : Original Image [4].

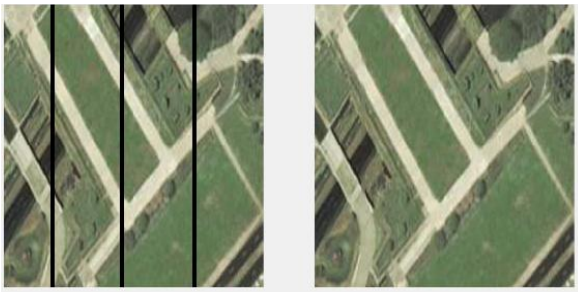

Figure 7 : Strip contaminated Image and Strip removal Image by Proposed Algorithm.

Figure 8 : Original Image.

Figure 9 : Scratch contaminated Image and Scratch Removal Image by Proposed Algorithm.

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Figure 10 : Original Image.

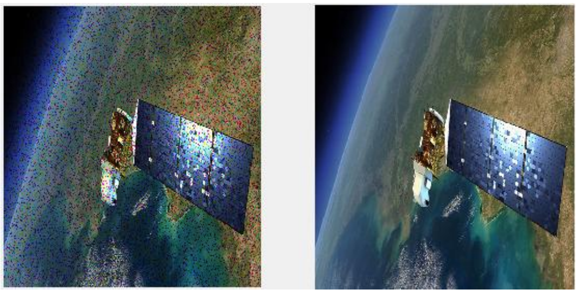

Figure 11 : Pepper and Salt noise contaminated Image and Pepper and Salt noise Removal Image by Proposed Algorithm.

Figure 12 : Original Image with noise added.

Figure 13 : The original image has been manually selected as target region.

Figure 14 : Mask (Target Region).

Figure 15 : Final image where selected Object has been completely removed and inpainted by Proposed algorithm.

Figure 16 shows PSNR,SSIM, metric Q values computed for six experiments.

TABLE 1 : PSNR,SSIM, metric Q values computed for six experiments by Proposed system.

	PSNR	SSIM	MQ
Noise	49.79575	0.927203	44.3157
Text	34.59166	0.94731	56.4534
Strip	32.49496	0.965093	66.55614
Scratch	35.13834	0.943507	55.18748
Object	36.05202	0.947942	96.3627
Pepper & salt	39.78164	0.940092	38.67448

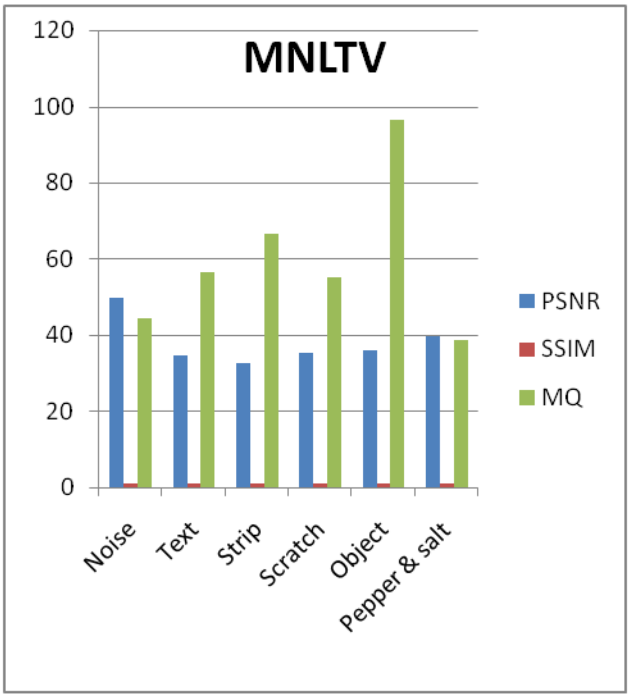

Figure 16 **:** shows PSNR,SSIM, metric Q values computed for six experiments.

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TABLE 2 describes various results of proposed system and existing systems in [18], on image data set as Image1, Image2 and Image3. For each system TABLE 2 shows calculation of PSNR and Execution Time in sec. By employing proposed system and existing systems for object removal it specify that despite the fact the proposed system gives not as much of PSNR values as compared to Existing Systems but Execution time required for object removal is very effective than Existing System as shown in Figure 17.

TABLE 2 : Performance Of Proposed System As Compared To Existing Systems for Object Removal.

Name of Input mage	Name of Systems	PSNR	Execution time in sec.
Image1	MNLTV	33.05635	49.7598
	LBP	63.20561	612.5056
	MEDIAN	63.04335	2526.073
Image2	MNLTV	36.05195	194.9464
	LBP	63.54569	917.4182
	MEDIAN	65.07123	2524.527
Image3	MNLTV	27.23474	78.70686
	LBP	62.78	397.5342
	MEDIAN	62.92245	1007.904

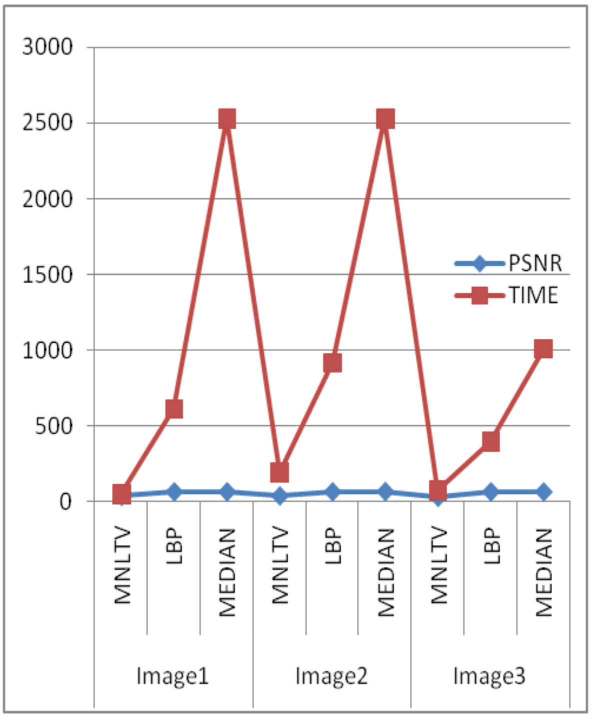

Figure 17 : Graph shows PSNR and Execution Time of an Images for Object Removal with proposed and existing Image Inpainting Algorithms.

V. CONCLUSION AND FUTURE SCOPE

This paper presents passive technique which can be deal with the remotely sensed image reconstruction problem. The proposed algorithm was applied to recovery of strip removal, unwanted map lettering removal from photographic map, removal of random dead pixels and remove object from image. All the simulated data experiments indicate that the reconstruction results using proposed algorithm are very effective.

Furthermore through an analysis the performance Of proposed system as compared to existing systems with the help of PSNR and Execution Time in sec. Contribution given in this paper is a new objective such as to remove text overprinted on an image, restoring images with scratches and remove the pepper and salt noise by means of proposed algorithm. Also, created a database of images in order to be able to test the efficacy of proposed technique.

An interesting extension of image inpainting would be to video inpainting. Also the inpainting algorithm presented here is not meant to be used for inpainting videos, there may still room for improvement of our proposed method to make it more robust so that it can be used with videos.

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