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Enhanced Image Inpainting in Remotely Sensed Images by Optimizing NLTV model by Ant Colony Optimization

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ABSTRACT- Filling dead pixels or eliminating unwanted things is typically preferred within the applications of remotely sensed images. In proposed article, a competent image imprinting technique is demonstrated to resolve this drawback, relied nonlocal total variation. Initially remotely sensed images are effected by ill posed inverse problems i.e. image destripping, image de-noising etc. So it is required to use regularization technique to makes these problems well posed i.e. NLTV method, which is the combination of nonlocal operators and total variation model. Actually this method can make use of the good features of non-local operators for textured images and total variation method in edge preserving for color images. To optimize the proposed variation model, an Ant Colony Optimization algorithm is used in order to get similarity with the original image. And evaluate the outcomes of proposed technique with the existing technique i.e. MNLTV optimized by Bregmanized-operator-splitting algorithm which is a prediction based method. The investigation of all outcomes confirms the efficacy of this rule.

Keywords- Inpainting, Regularization, Nonlocal total variation, Multichannel nonlocal total variation, remotely sensed images.

1. INTRODUCTION

Remote sensing makes it possible to collect data of dangerous or inaccessible area which cannot be done manually. Remote sensing includes monitoring deforestation and many other applications. Remote sensing data are being employed today in a wide variety of modeling activities. While remotely-sensed data are used in assembly maps, they are also being enrol to calculate a variety of environmental parameters. Remotely sensed satellite data comes in two different ways, passive data and active data as in passive, information assortment aims on obtaining intensities of radiation made by the sun and mirrored off the surface of the world. Active information assortment is basically incommodious to devices that dispatch and turn out a pulse of energy thereto is remand to the satellite to be recorded. Most of the volitionally procurable information is passively collected and is incommodious to energy not absorbed by the Earth's atmosphere Dr. Lie (2001). Satellite representational process supported passive reflectivity in four ways in which, that area unit visible, infrared, multispectral, and hyperspectral .Sometimes while capturing the image dead pixels or some kind of noise may exist in the image which corrupts the image so our aim is to remove the noise from the image and make it clear for human perception. And sometimes it is necessary to remove some part of the image to make the image much clear and noise free so we can done this type of work by using inpainting process Cheng and Shen (2014). Now in this paper, first of all we have to remove the ill posed problems like image destripping, reconstruction and any more. This is done by using Regularization method. Regularization is a method which we mostly used for image processing for image de-noising. There are two types of regularization methods.

(a) Local methods (b) Nonlocal methods

Local methods recover pixels by using the local neighboring information. Local methods are image smoothing, adaptive filters and total variation method. Local techniques are well especially for geometric shapes like image corners or edges.

Non-local methods recover all the pixels of the image one by one depending upon thresholding value. If the variation value is less than the threshold value than it means there is no noise present on the image and if it is more than the threshold value then we have to make closer to the threshold value. Non local methods are NLTV, MNLTV, N-L (Nonlocal) means algorithm. Inpainting techniques are currently a great deal well likeable currently a days, particularly in remotely detected images wherever there's terribly tough to eliminate parts or to get rid of noise like speckle impairment of noise. AR images are primarily pretentious by speckle impairment noises that is extremely tough to get rid of. Adaptive filters will be accustomed scale back the speckle disturbance but the utilization of filters that are adaptive needs of process power to beat downside use denoising filter has been done and called NL-means. Later than, non-native strategies such as NLTV who can maintain each geometrical details like edge and surface information. Dead pixels are unnecessary pixels within the illustration or image that ends up in corrupted image. Utmost a technique is extremely a lot of capable of exclude the dead pixels as of a representation and additionally carried out for image destripping referred as posteriori (MAP). A MAP algorithm build operational work of neighbor a periori restriction and provides specified outcome as discussed by Shen, Tinghua, Pingxiang (2008). The uncomplicated method of destripping is make use of LPF in occurrence freq field. However downside of method is that it cannot exclude whole stripes from the image and therefore ends up in blurring. Riffle technique can additionally be used for destripping which may simply observe and take away stripes in an image however during these some irregularities also happens. To manage this downside we've got finite impulse response filter. Generally images masked by blur shade. To eliminate blur shades. Annulet primarily elide inpainting has been employed. However reported methodology has high process quality thence not used. Quality and purity of the representation based on quantities like PSNR (maximum peak signal to disturbed noise ratio), SSIM (Structural resemblance index unit), and Q-metric. Parameter of SSIM varied from zero to one. Higher the standards of those quantities a lot of sensible are the standard that's to mention, our projected methodology will achieve each the mode (spatial) and the spectra consistency or coherence. For optimizing the projected NLTV form, Ant Colony improvement formula is taken into consideration. The article is discussed given below. In research section 2, the total variation technique is explained. MNLTV is explained in Section 3 and NLTV in IV. The Ant Colony Optimization is given in Section 5. Section 6 show the investigational outcomes and Section 7 represents wrapping up of article with conclusion.

2. TOTAL VARIATION MODELS

2.1 TV (Total Variation)

Total variation denoising is additionally referred to as total variation regularization. Regularization could be a technique that is generally utilized in technique of digital image process also has advantage of distortion exclusion explained in Mr. Patel and Prof. Desai (2011). Depends on integrity to facilitate data through imprudent and presumably specious data include more entire fluctuations, i.e. the essential of absolutely the slope of the indicator is inflated. Functioning of particular technique, minimizing complete fluctuation of the signal results in detailed alikeness to first signal eliminates undesired knowledge, whereas protects major details like edges. Total variation essentially estimates what quantity the signal changes between signal values, and has regularization parameter, λ which manages how much smoothing is executed (Dahl, Hansen, Jensen, 2009). Algorithms This noise removal technique is very effective in preserving edges during smoothing and reduces disturbance at lesser SNR.

Total fluctuation is defined as (https://en.wikipedia.org/wiki/Total_variation_denoising).

$$V(y) = \sum_n |y_{n+1} - y_n| \tag{1}$$

Given input signal x_n, the aim of this method is to find estimation, y_n

$$E(x,y) = ½\sum_n (x_n - y_n)^2 \tag{2}$$

2.2 MNLTV (Multichannel Nonlocal Total Variation)

MNLTV (Multichannel nonlocal total variation) method is basically the extended version of NLTV model as explained by Cheng and Shen (2014). This technique takes advantages of the multichannel information of remotely detected images. It's accustomed tackle with the remotely detected image for reconstruction drawback. This technique takes the options of a nonlocal operators, which encompasses a superior interpretation, once associating with rough images and freshen up large-scale regions.

$$J^{w}_{MNLTV}(u) := \sum_{x \epsilon MXN} \sqrt{\sum_{j=1}^{B} \left|\Delta_{\omega} u_j(x)\right|^{2}} = \sum_{x \epsilon MXN} \sqrt{\sum_{y \epsilon MXN} \left|u_j(x) - u_j(y)\right|^2 \omega(x,y)}. \tag{3}$$

2.3 NLTV (Nonlocal Total Variation) - Proposed Model

As discuss above that, Regularization method is of two types. Local methods are good for preserving edges but nonlocal methods have much more superior performance when dealing with textured images and protective edges that's why Nonlocal ways area unit far better than native ways. NLTV is the combination of nonlocal operators and Total variation model. This methodology will create employment of the immense efficiency of nonlocal operators in surface images and Total variation methodology for edge protective for color images (Duan, Pan, Liu, & Tai, 2013). The NLTV model solely consist single changeable and one penalty limitation in its force practical and this form repeatedly brought about abundant simple machine method plus conjointly offers wonderful outcomes in retentive texture of grey images. Though, greatest of mastery, this counseled form (technique) cannot take into account for color image inpainting.

Non local filter: In this paper, we are interested in NLTV because, analogous to classical TV, the $L1$ norm is generally more efficient than the $L2$ norm for sparse reconstruction as explained by Goldstein & Osher

(2009). Basically nonlocal filters take the advantage of high degree of redundancy of natural images and If we compare the results of non-local filters with different well-known denoising techniques, like Gaussian filter, the anisotropic model, the overall variation denoising technique, the Wiener filter but Nonlocal filters eliminates noise more effectively from the image than the any other local methods. Recently non-local suggests that has been enlarge to different image process applications like interlacing and examine interpolation. Non local gradient$\Delta_\omega u(x,y)$: $\Omega \rightarrow \Omega \times \Omega$ is explained by Cheng and Shen (2014). The vector of all partial derivatives $\Delta_\omega u(x,.)$ at x such that

$$(\Delta_\omega u)(x,y):=(u(y)-u(x))\sqrt{\omega(x,y)}, \forall y\epsilon\Omega. \quad (4)$$

$$J^w_{NLTV(u):=}=\sum_{x\epsilon\Omega}|\Delta_\omega u(x)| =$$

$$\sum_{x\epsilon\Omega}\times\sqrt{\sum_{y\epsilon\Omega}\left(u(x)-u(y)\right)^2}\,\omega(x,y). \quad (5)$$

3. OPTIMIZATION

The Ant colony method for image processing introduced in Marco and Stutzle (2004). Now in this paper, NLTV method is optimized by Ant colony optimization method to make images more clear. Basically Metaheuristic algorithms are algorithms those who flee from native optima, drive some basic heuristic: either a constructive heuristic ranging from a null answer and adding components to create a decent complete one, or a neighborhood search heuristic ranging from an entire answer and iteratively modifying a number of its elements so as to attain a far better one. The metaheuristic half permits the low level heuristic to get solutions higher than those it might have achieved alone, even if iterated.

$$p_{i,j}=\frac{(\tau^{\alpha}_{i,j})(n^{\beta}_{i,j})}{\sum(\tau^{\alpha}_{i,j})(n^{\beta}_{i,j})} \quad (6)$$

$\tau_{i,j}$-Pheromone concentration on edge i,j
α-Parameter to control the influence of $\tau_{i,j}$
$n_{i,j}$-Desirability of Edge i,j
β- Factor to control influence $n_{i,j}$

The optimization process of the ACO (Any colony optimization) method is described in Algorithm by (Haitham, Karl, & Michael, 2012).

Algorithm: Ant Colony Optimization

1: Initializing pheromone level $\tau_{i,j} \leftarrow \tau_o \forall(i,j) \in E$
2: Choosing the initial vertex $v_{start} = i \in V$
3: **for** iteration t=1, 2…
4: **for** ant m=1, 2….
5: $v_{pos} = v_{start}$ and $v = \{\}$
6: **While**∃practicalprotraction (v_{pos}, j) of u **do**
7: Choose j corresponding to $p_{i,j}$, where
8: $p_{i,j}=\begin{cases} 0 & if\ (i,j)\ infeasible \\ \frac{(\tau^{\alpha}_{i,j})(n^{\beta}_{i,j})}{\sum(\tau^{\alpha}_{i,j})(n^{\beta}_{i,j})} & Otherwise \end{cases}$
9: $u = u\oplus(v_{pos}, j)$ and $v_{pos} = j$
10: Updating the Pheromone trail $\tau_{i,j}$ by Eq. (7)

Supposing there occurs a possible way to the target, additional imaging that the diagram is associate degree random set if the target situation is vanished, then all ants are soaked in this target situation in ample time.

$$\tau_{i,j}(t+1) = (1-\rho)\tau_{i,j}(t) + \sum_{m=1}^{M}\delta_{i,j}(t,m), \quad (7)$$

$\tau_{i,j}$- Amount of pheromone on edge i,j
ρ- Pheromone evaporation rate
M-No of ants
$\delta_{i,j}(t,m)=Q\,\frac{n_{i,j}}{L}$
Where Q is invariable & L is the whole range.
Q=$\frac{1}{M}$, maintain abounded sum for an arbitrary no of ants

Ant Colony optimization has been and remains to be a helpful procedure for coming up with effectual combinatorial optimization resolution algorithms. When the lasting of studies, each its supplication effectiveness and its abstract groundings are incontestable, creating ACO one among the foremost victorious procedure within the metaheuristic space. ACO is optimization based method and it also improves the quality of the channel. Suppose we have three channels and this method adapts all the channels one by one and make it suitable for its operation. Whether in case of BOS method it just predicts the channel not improves the quality of the channel.

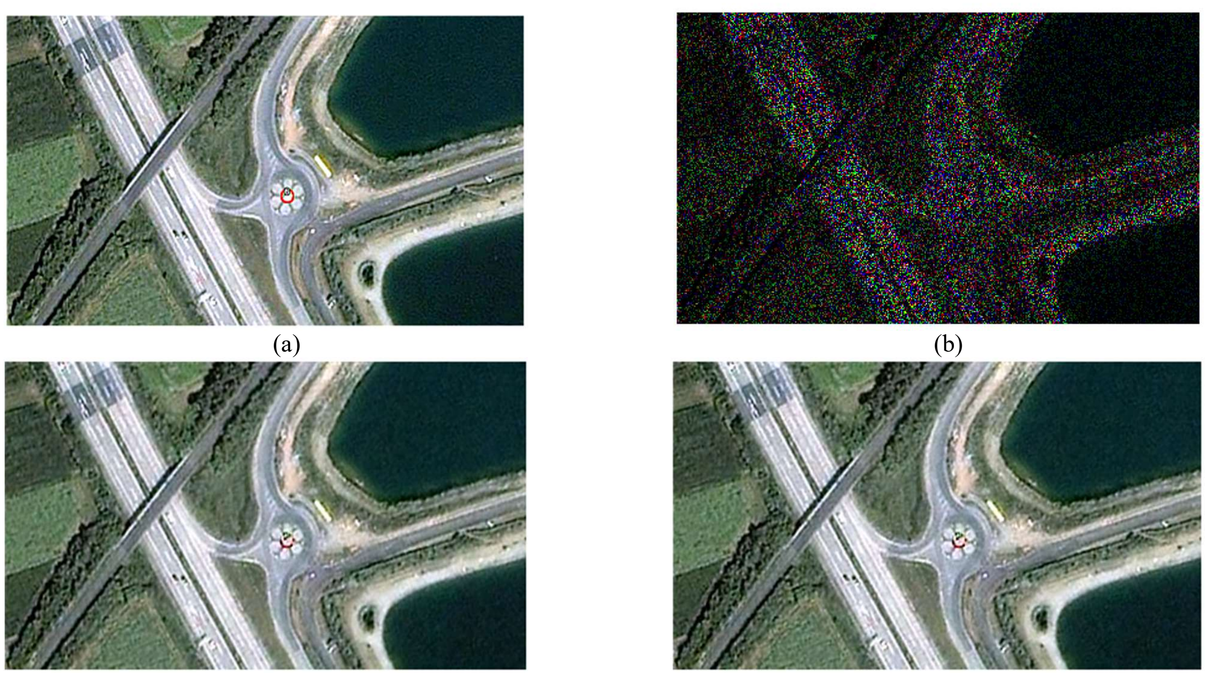
4 EXPERIMENTS

4.1 Simulation and evaluation: In performed experiments, we tend to performs associate degree experiment to check and validate the effectuality of current projected NLTV inpainting rule. Results of the experiment as shown in Figs1-2, are quite similar to each other from visual side but the parameters of our proposed method are improved as shown in Table 1. First one is original image then we've wheezy images therefore we've to recover the image by two totally different ways. Image ‘c’ is recovered by using MNLTV (multichannel nonlocal total variation) method, the noise is excluded from the image but this illustration is not properly recovered due to loss of image details. But the image‘d’ is much more clear than the MNLTV method without the loose of any image details. The resultant images for both the methods are quite similar from visual scene but the results of our proposed method are improved as shown in table 1.

(a) (b) (c) (d)

Fig.1-Inpainting experiment for noise elimination (a) Authentic image. (b) Contaminated noise image (c) MNLTV model (d) NLTV technique optimized by ACO

So according to resultant image of NLTV optimized by ACO is more effective than MNLTV method. The peak S/N (PSNR) catalog is employed to find highest peak value in an image of the performed experiments from the gray-level reliability aspects. Now we have another example of remotely sensed image as shown in Fig 2.This Image is also have the same result as Fig 1. In this NLTV is again very effective if we compare it with MNLTV method.



(a) (b) (c) (d)

Fig.2- Inpainting experiment for noise elimination (a) Authentic image. (b) Contaminated noise image (c) MNLTV technique (d) NLTV technique optimized by ACO

Now we have another example of remotely sensed image as shown in Fig. 2. This Image is also has the same result as Fig 1. In this NLTV is again very effective if we compare it with MNLTV method. Now comes to Fig 3 in which we test our proposed method on grey scale image. As you can see in ‘c’, this also shows the same effect as this method for colored remotely sensed images. In this, again MNLTV method loses too much details from the images and leads to blurring but there is no such blurring in the case of NLTV and there is again no loss of any geometric details. For image PSNR plays terribly effective role. PSNR is most often used to cypher the attribute of re-enactment of less energy contraction codec’s. Genuine or original information comes with current technique, the disturbance is disturbance imitated due to contraction. Once different compression codec’s, PSNR is associate estimation to human perception of reconstruction quality. While the next PSNR ordinarily specify that the reconstruction is of upper quality, in some cases it should not.

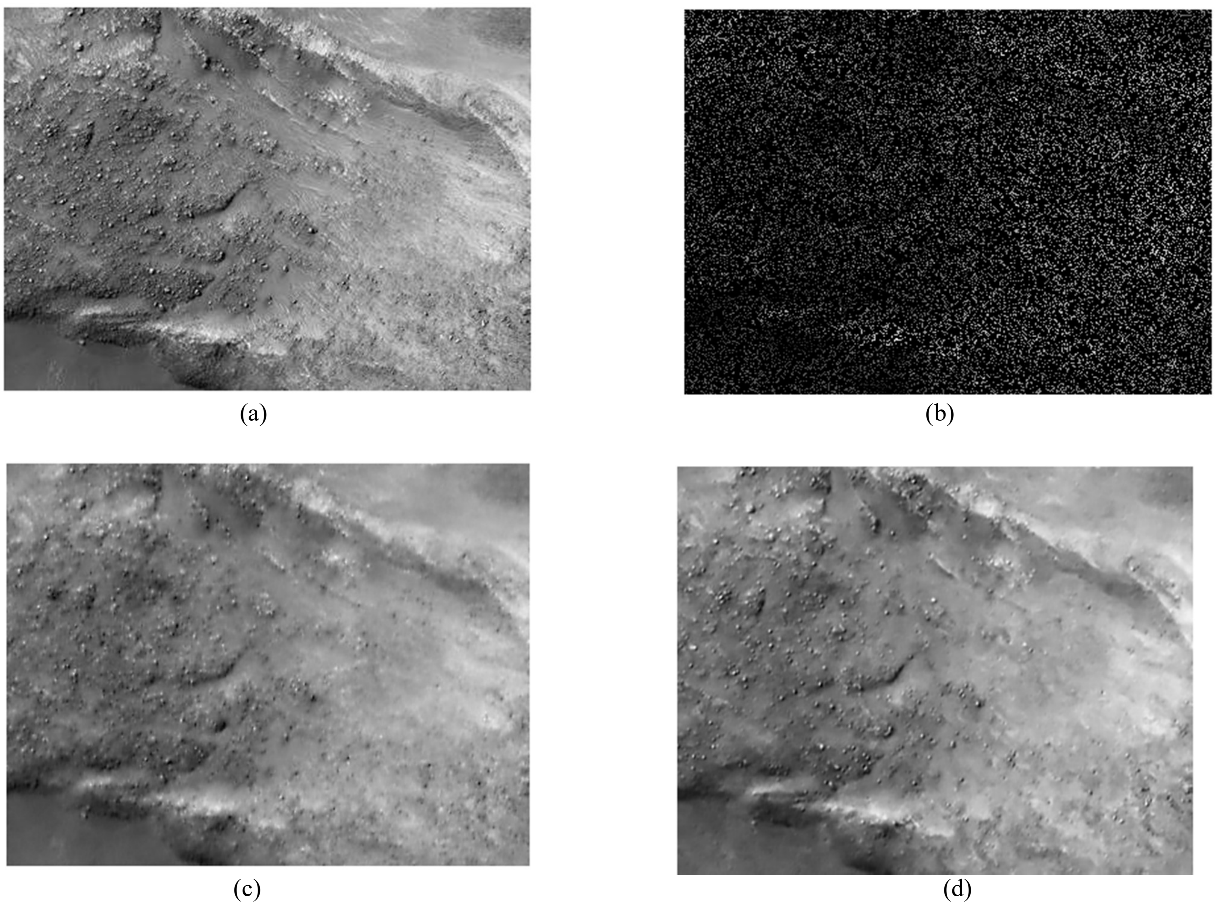


Fig.3- Inpainting experiment for noise elimination for grey scale image (a) Authentic image (b) Contaminated noise image (c) MNLTV technique (d) NLTV technique optimized by ACO

In Fig 3 in which we test our proposed method on grey scale image. As you can see in ‘c’, solid dust particle are just diffused into the image and the image gets blurred but in ‘d’ it retains there. In this, again MNLTV method loses much details from the images and leads to blurring but there is no such blurring in the case of NLTV and there is again no loss of any geometric details. For image, PSNR plays very important role, more the value of PSNR more better will be the standard. PSNR is majorly operate to calculate the re-enactment of lesser energy contraction codec’s. Genuine or original information comes with current technique, the disturbance is disturbance imitated due to contraction. During different compression codec’s, PSNR is associate degree estimation to human opinion of reformation quality whereas better PSNR usually specify that, reconstruction is of upper quality, in a few studies it shouldn’t.

Table 1: PSNR, MSE, SSIM AND METRIC Q values of Simulated Experimental Results

	Parameters	MNLTV	NLTV
Fig.1	PSNR	30.589	31.483
	MSE	5.3121	3.4142
	SSIM	0.91767	0.92715
	Q	61.178	61.342
Fig.2	PSNR	27.2242	27.8272
	MSE	6.3389	4.1503
	SSIM	0.81673	0.93895
	Q	54.4485	55.0051
Fig.3	PSNR	23.9366	25.4355
	MSE	8.1656	5.764
	SSIM	0.7181	0.76412
	Q	47.8731	50.871

Apart from PSNR and MSE there are also other two parameters SSIM (Structural similarity index module) which tells us about how much the recovered image differs from original image.

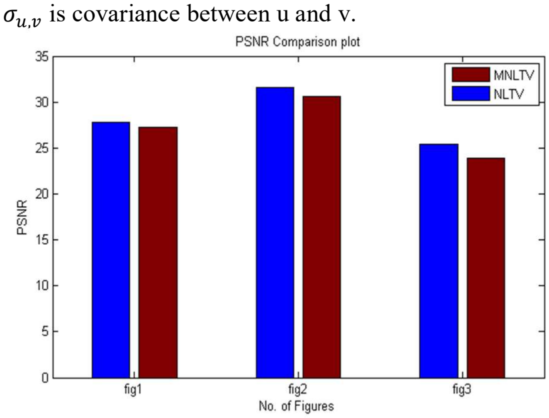
$$\text{SSIM}(u, v) = \frac{(2\mu_u\mu_v + C1)(2\sigma_{u,v} + C2)}{(\mu_u^2 + \mu_v^2 + C1)(\sigma_u^2 + \sigma_v^2 + C2)} \quad (8)$$

Where C1=$(K_1L)^2$, C2=$(K_2L)^2$, $K_1 = 0.0.1$, $K_2 = 0.0.3$ $\sigma_{u,v}$ is covariance between u and v.

σ_u^2, σ_v^2 are the variances of original and recovered image. And Q metric value basically tells you the quality of an image.

$$Q = S_1 \frac{S1 - S2}{S1 + S2} \quad (9)$$

Where S1 and S2 are the singular metrics of gradient matrix of recovered image.



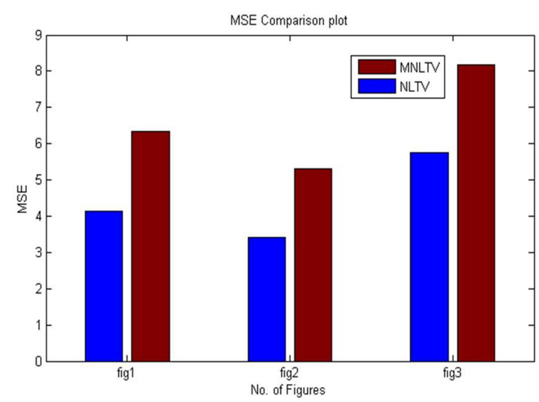


Fig.4- Comparison Graphs b/w MNLTV and NLTV method (a) MNLTV Versus NLTV for PSNR values (b) MNLTV Versus NLTV for MSE values

The efficiency of the projected NLTV inpainting methodology may additionally elucidate by the parametric evaluation. PSNR and MSE standards of all the experimental figures shows you that how much both are methods are different from each other in terms of textures and clarity of an image. All simulated information experimental outcomes specify that the projected NLTV methodology optimized by ACO will offer us a stronger robust and more powerful inpainting result. Two of the false metrics won't to evaluate the varied contraction techniques square measure the Mean sq. PSNR. The MSE is that the sq. of the distinction between square error original image and contracted image, whereas PSNR may be a gauge of the height error. Equation for every the parameters square measure:

$$\text{PSNR} = 10log_{10}\frac{255^2 * MN}{\|\hat{u} - u\|^2} \quad (10)$$

$$\text{MSE} = \frac{1}{MN}\sum_{y=m}^{M}\sum_{x=0}^{N}[I(x,y) - I'(x,y)]^2 \quad (11)$$

I(x, y) is Raw image, I'(x, y) is that the denoised image and MN are the entire no of pixels of the photographs. The basic relation between the MSE and PSNR is that, they are inversely proportional to each other. If you have more value of MSE then automatically you have lower value of psnr and low value of psnr means image quality will be bad and vice versa. Logically, a bigger value of PSNR is nice as a result of it defines that the quantitative relation of Signal to Noise is higher than why PSNR should be high. And in PSNR we concentrate only on peak value i.e. high intensity regions rather than low intensity regions.

5. CONCLUSION

In this paper, we present an NLTV inpainting model to deal with the ill posed inverse problems such as image stripping, image denoising for remotely sensed images. We regularize these ill posed inverse problems by NLTV method and then we optimize the NLTV model by Ant Colony Optimization in order to get the better quality image. The proposed method is applied to number of images and the experimental results of our proposed method are very effective than the MNLTV model either in terms of textures or capability to eliminate noise.

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