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IMAGE DENOISING: A MULTI-SCALE FRAMEWORK USING HYBRID GRAPH LAPLACIAN REGULARIZATION

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Abstract— in this paper main aim is to focus on to remove impulse noise from corrupted image. Here present a method for removing noise from digital images corrupted with additive, multiplicative, and mixed noise. Here used hybrid graph Laplacian regularized regression to perform progressive image recovery using unified framework. by using laplacian pyramid here build multi-scale representation of input image and recover noisy image from corser scale to finer scale. Hence smoothness of image can be recovered. Using implicit kernel a graph Laplacian regularization model represented which minimizes the least square error on the measured. A multi-scale Laplacian pyramid which is framework here proposed where the intra-scale relationship can be modelled with the implicit kernel graph Laplacian regularization model in input space inter-scale relationship model with the explicit kernel in feature space. Hence image recovery algorithm recovers the More image details and edges

***Keywords**:*- impulse noise, graph laplacian regularized regression, multi-scale framework.

I INTRODUCTION

The recovery of image from corrupted observation is the problem that encouraged in many engineering and science applications, consumer electronics to medical imaging. In images contains noise that should be removed to improve quality of image. There are various types of noise that contains in image among this most frequently happened noise is the impulse noise, which occur in image during acquisition and transmission. It is one of the challenging task in image processing to restore original image from noisy version. The pixel corrupted by noise and remaining is noise free is an important characteristic of impulse noise and Hence, in proposed work focus on the impulse noise.[1]

One challenging image processing problem is to removing impulse noise from images, because scan line are highly salient features for visual attention. During impulse noise removal, one important requirement is to preserve image structures, such as edges.

II LETURATURE SURVAY

There are various methods to remove impulse noise. The results of the noise removal depends the quality of the image processing technique. In image processing there are various technique are established for noise removal. The problem occurs during noise removal is depends on the type of the noise corrupting the image. For the reduction of the noise from the image there are various filtering methods such as linear and non-linear filtering method.

Using filter noise is removed from image. To remove impulse noise is one of the fundamental challenge for linear methods. To achieve the target of noise removal, low-pass filtering is used in these remove the high-frequency components of images. For smoothing of image it is very effective.[2] But the low-pass filtering introduces large, spurious oscillations near the edge such as Gibb's phenomena for texture and detail regions. decision-based filters is most popular non-linear filtering method which is used to achieve effective performance. These filter firstly apply impulse noise detector that determine filter pixel and then replace them using median filter and other remaining pixel are unchanged. for these task the adaptive median filter (AMF) and the adaptive center-weighted median filter (ACWMF) also represented.

III EXISTING METHOD

Recovering images from noise forms is an ill-posed inverse problem. It is calculate as an energy minimization problem in which more accuracy is the goal. The performance of an image recovery algorithm depends on how better it apply regularization conditions or priors when numerically solving the problem, because the useful prior statistical knowledge can regulate estimated pixels.

Figure 1 Intra-scale and inter-scale correlation.

Intensity consistency is common prior assumption for natural images that means nearby pixels and pixels on the same structure have the same or similar intensity values. These assumption means images are locally smooth and have the property of non-local self-similarity.

From observation, to keep the local smoothness of images we inspires to learn and propagate the statistical features across different scales. In image processing, the non-local self-similarity of images is resource to attracted increasingly more attention. From Figure 1 In intra-scale correlation, image patches repeat themselves in the whole image plane it is based on non-local self-similarity.[3]

The semi-supervised learning gives inspiration to address the problem of image recovery. In semi-supervised learning uses both lable and large amount of unlabeled data.

IV PROPOSED SYSTEM

In proposed method construct powerful algorithm to perform image recovery using hybrid graph laplacian regularized regression. In this we use multiscale framework of input image to combine local smoothness and non-local self-similarity by laplacian pyramid. Using implicit kernel a graph Laplacian regularization model represented which minimizes the least square error on the measured. A multi-scale Laplacian pyramid which is framework here proposed where the intra-scale relationship can be modeled with the implicit kernel graph Laplacian regularization model in input space inter-scale relationship model with the explicit kernel in feature space.

V IMAGE RECOVERY USING GRAPH LAPLACIAN REGULARIZED REGRESSION

A. *Problem description*

Given a noisy image **X** with n pixels, its feature vector **x**i = [**u**i,**b**i] ∈ _m+2,is described for each pixel. Where **u**i is the coordinate and **b**i is a certain context of **x**i which is defined differently for different tasks. [4]

To remove impulse noise from image, two steps are implemented to improve the performance of image:

firstly use *ad*aptive median filter or its variant to differentiate noise and clean the samples. After that noise free pixels are labled with intensity value remain same and noisy pixels are unlabeled with intensity value is re-estimated. In second phase, for labled pixels adjust the inference to give a best fit and for unlabeled pixels use fitted model

B. *Graph Laplacian Regularized Regression (GLRR)*

For giving re-estimated value of noisy pixels here derive prediction function *f*. In the set of labeled pixels prediction function f is learned to minimize prediction error.

These is formulated as follows:

$$\arg\min_{f\in\mathcal{H}_\kappa} J(f) = \arg\min_{f\in\mathcal{H}_\kappa} \sum_{i=1}^{l} \|y_i - f(\mathbf{x}_i)\|^2 + \lambda\|f\|^2, \quad (1)$$

Where *Hκ* is the Reproducing Kernel Hilbert Space (RKHS)to calculate conclusion this regression model use only labled sample. But the time of less labeled sample means noise level is high it cannot recover the noisy image. Hence its to maintain intrinsic geometrical structure of the image data.

There are large amount of unlabeled samples, the semi-supervised learning use the large amount of unlabeled data to capture the information for generalization. Hence the semi-supervised learning utilize large amount of labeled and unlabeled data to achieve better result. Here we use manifold assumption to use unlabeled sample that is implemented by graph structure. In this create exact copy of noisy image as undirected graph ,in that graph vertices are data points and edges shows the relationship between vertices. To show the similarity between that vertices every edges have assigned a weight. From above, the graph laplacian is described for the intrinsic geometrical structure of the data space. Mathematically, For minimizing the following term the manifold assumption can be implemented as:

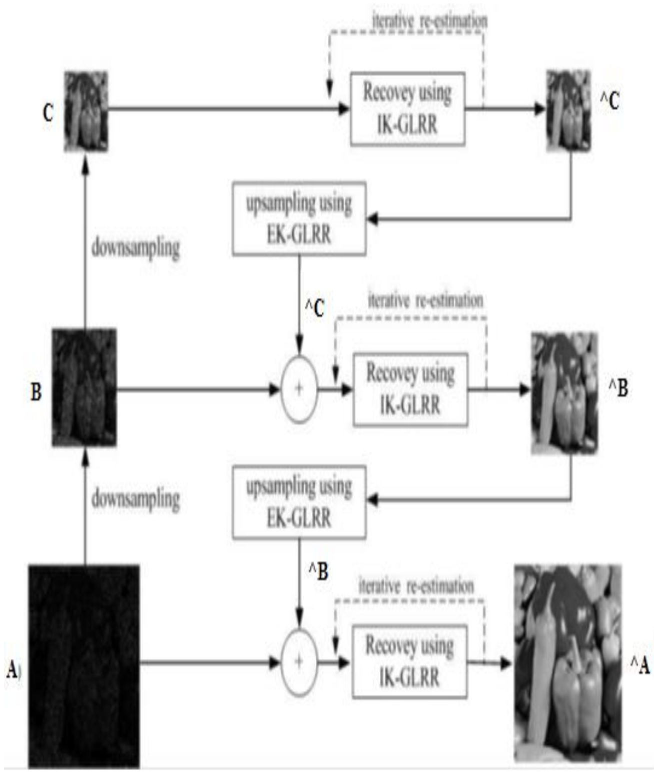

Figure 2 Diagram of proposed method

$$R(f) = \frac{1}{2}\sum_{i,j}^{n} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2 \mathrm{W}_{ij}. \qquad (2)$$

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where W_{ij} is edge weight between two vertices **x**i and **x** j. edge weights play a important role for graph construction. Here for design edge weights, combine bilateral filter and the non-local-means weight having the edge-preserving property and robust property respectively, which are defined as follows:

$$\mathbf{W}_{ij} = \frac{1}{C}\exp\left\{-\frac{||\mathbf{u}_j - \mathbf{u}_i||^2}{\sigma^2}\right\}\exp\left\{-\frac{||\mathbf{b}_j - \mathbf{b}_i||^2}{\varepsilon^2}\right\}, \quad (3)$$
$$\sigma > 0, \varepsilon > 0.$$

Where **b**i (**b**j) is defined as the local patch centered on **u**i(**u**j). The first term and the second term is considers as geometrical and the structural similarity.[6]

Now we define graph laplacian as **L** = **D** − **W**. here, D is diagonal matrix and this diagonal elements are row sums of W. From this equ.(2)can be written as:

$$R(f) = \sum_{i=1}^{n} f(\mathbf{x}_i)^2 \sum_{j=1}^{n} \mathbf{W}_{ij} - \sum_{i,j}^{n} \mathbf{W}_{ij} f(\mathbf{x}_i) f(\mathbf{x}_j)$$
$$= \mathbf{f}^T\mathbf{D}\mathbf{f} - \mathbf{f}^T\mathbf{W}\mathbf{f} = \mathbf{f}^T\mathbf{L}\mathbf{f}, \quad (4)$$

Where **f** = { f (**x**1), . . . , f (**x**n)}. To obtain the objective function of Laplacian regularized least square (LapRLS) we combine the above regularization term with Eq.(1) as:

$$\arg\min_{f \in \mathcal{H}_\kappa}\{J(f) = \|\mathbf{y}_L - \mathbf{f}_L\|^2 + \lambda\|f\|^2 + \gamma\mathbf{f}^T\mathbf{L}\mathbf{f}\}, \quad (5)$$

C. Optimization by Implicit Kernel

To obtain the solution for above function we use the property of RKHS called as representer theorem. Firstly, we use representer theorem for labeled sample that allows to obtain solution of regularized least square (RLS) that is formulated in equ.(1) for the terms of labeled data and kernels. Following is representation of theory as:

Figure 3 seven sample images in the test set

Table 1 Objective quality comparison of four algorithms for salt-and-pepper noise removal

Images	80%				85%				90%			
	KR	Cai	IFASDA	Our	KR	Cai	IFASDA	Our	KR	Cai	IFASDA	Our
lena	30.08	27.54	28.32	30.09	30.03	27.53	28.54	30.42	29.81	27.86	28.54	30.37
barb	30.03	27.53	28.37	30.2	29.7	27.64	28.32	30.04	29.76	27.7	28.59	30.26
Man	29.76	27.48	28.48	30.2	29.76	27.59	28.43	30.09	29.76	27.7	28.65	30.2
Sai	29.87	27.81	28.37	30.26	29.7	27.7	28.48	30.04	29.98	27.64	28.4	30.09
Bubble	29.7	27.7	28.7	30.37	29.7	27.81	28.44	30.04	30.03	27.81	28.32	30.31
Anna	29.87	27.75	28.54	30.09	29.81	27.75	28.59	30.42	29.65	27.82	28.32	30.42

$$f(\mathbf{x}) = \sum_{i=1}^{l} \alpha_i \kappa(\mathbf{x}_i, \mathbf{x}).$$

But in above model we use only labeled samples. Hence to utilize both labeled and unlabeled samples here extend RLS to LapRLS that is formulated in equ. (5). Following mathematical model shows the extended version of representer theorem that utilize both labeled and unlabeled samples as:

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i \kappa(\mathbf{x}_i, \mathbf{x})$$

D Optimization by Explicit Kernel

In this, reformulate the proposed graph laplacian regularized model in linear manner by mapping samples to a high dimensional space.

VI PROGRESSIVE HYBRID GRAPH LAPLACIAN REGULRIZATION

Here, use a simple multi-scale framework to achieve a purpose of proposed method. There are various reasons to use the multi-scale framework. Firstly here comparison of structures at different scales is one of the important characteristic of natural images. Secondly, this encodes low frequency parts and high frequency parts separately that give the compact representation of imaginary data using a multi-scale scheme. Third , four image blocks are merged into one block because of this stronger correlations between adjacent image blocks will be captured in the down sampled images.[7]

The above figure shows the Laplacian pyramid called as tree level laplacian pyramid. In this proposed method, we combine hybrid models and the multi-scale paradigm to recover the noisy imagery data. In figure 2 shows the multicale framework of test image pepper in that 90% of samples are corrupted due to noise, in this to show the levels of pyramid we use subscript l .

At starting we have the image **C** at scale 2 which defined coarser grid of pixel this image is recover using implicit kernel-graph laplacian regularized regression and unsampling of this recovered image using explicit kernel- graph laplacian regularized regression. In this experiment, to improve efficiency of processing result two iteration was found.

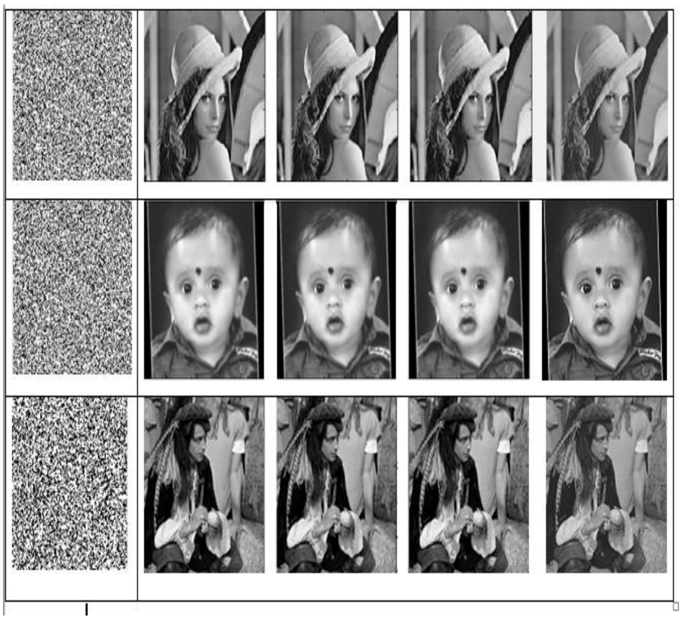

Figure 4 quality comparison on salt-and-pepper noise removal with the noise level 90%. Column 1: the noisy images; Column 2: the results of KR; Column 3: Cai's results; Column 4: the results of IFASDA; Column 4: regularized regression result results

In this proposed work the first contribution is maintain the intrinsic manifold structure by using labeled and unlabeled data. This is useful for removing impulse noise from images. The second contribution is the property of scale-invariant of natural image.

VI EXPERIMENTAL RESULTS AND ANALYSIS

Here, experimental results are presented to show the effectivity of the proposed algorithm on the task of impulse noise removal. In this project, we test two cases: only denoising and both denoising and deblurring, to show the effectivity of this method on handling impulse noise. For these two cases, here test two kinds of impulse noise: salt-and-peppers noise and random-valued impulse noise

For comparison, the proposed algorithm is compared with some state-of-the-art work. More specifically, four methods are included in this comparative study: (1) kernel regression (KR) based methods (2) two-phase method proposed by Cai (3) iterative framelet-based method (IFASDA) proposed by (4) proposed method (graph laplacian regularized regression.

In this work firstly, use the adaptive median filter (AMF) for salt-and-peppers noise detection, and use the adaptive center-weighted median filter (ACWMF) for random-value noise detection. Suppose that f be a noisy image with impulse noise and y be the filtered result by median-type filter, A be the image plane. the noisy pixels happened due to impulse noise can be shown as follows:

1] For salt-and-peppers noise:

$$\mathcal{N} = \{(i, j) \in \mathcal{A} : y_{ij} \neq f_{ij} \text{ and } f_{ij} \in \{d_{\min}, d_{\max}\}\},$$

2] For random-valued impulse noise:

$$\mathcal{N} = \{(i, j) \in \mathcal{A} : y_{ij} \neq f_{ij}\}$$

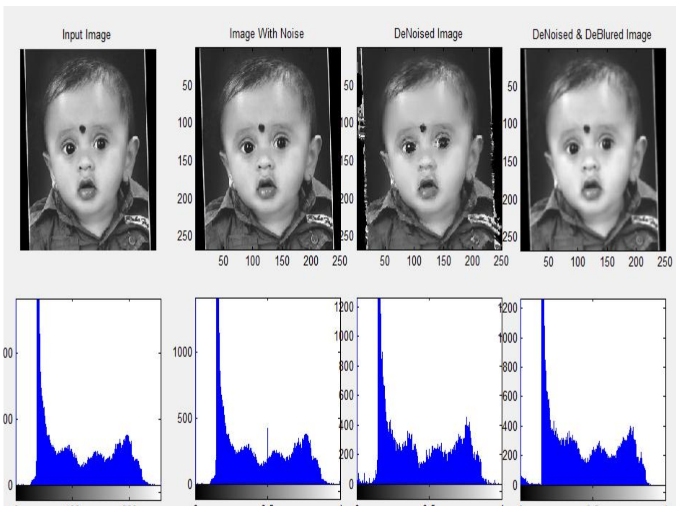

Figure 5 Histogram of Sai for salt and papper noise at noise level 90%

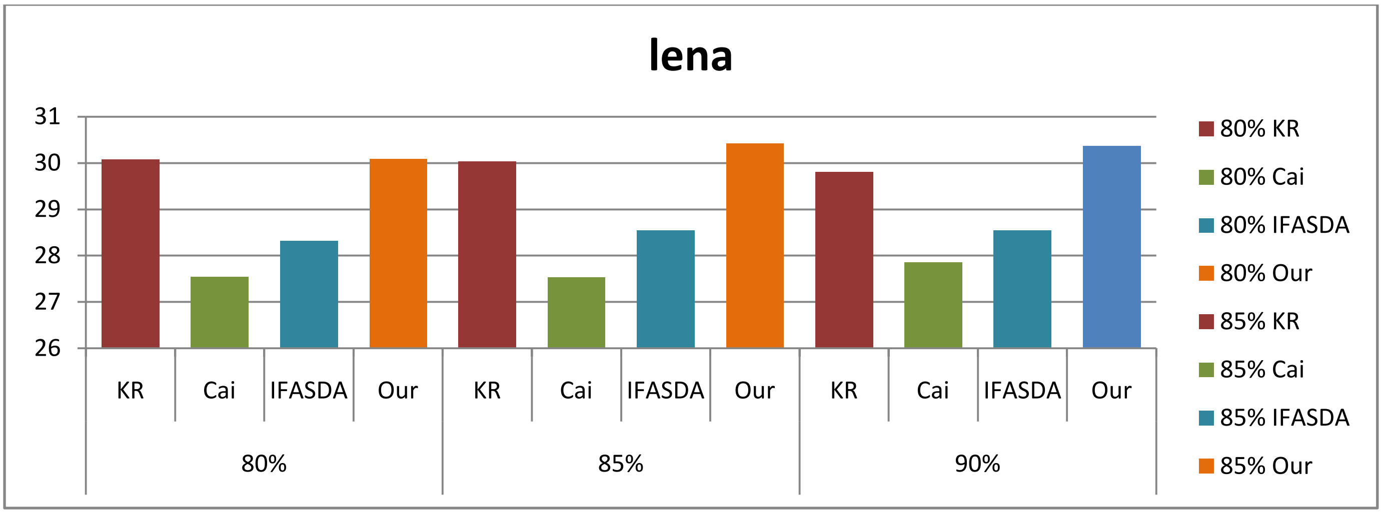

Figure 6 Bar chart for lenaimage to show quality comparison of KR, Cai, IFASDA Method with proposed method for salt and papper noise.

Then the detected noisy pixels are called as missing pixels (filled with 0) and the remaining clean pixels are kept their original value.

A. Salt-and-Pepper Noise Removal

Here, first compare performance of restored images that contain only salt-and-pepper noise. All test images are corrupted by salt-and-pepper noise with noise level : 80%, 85%. 90%. We use adaptive median filter to detect salt-and-pepper noise from image that shown in figure 4. It is clear that all images in data set gives higher performance of PSNR values as compared with existing methods. For sai, it also shows the effective performance of histogram with compared method that are shown in Figure 5

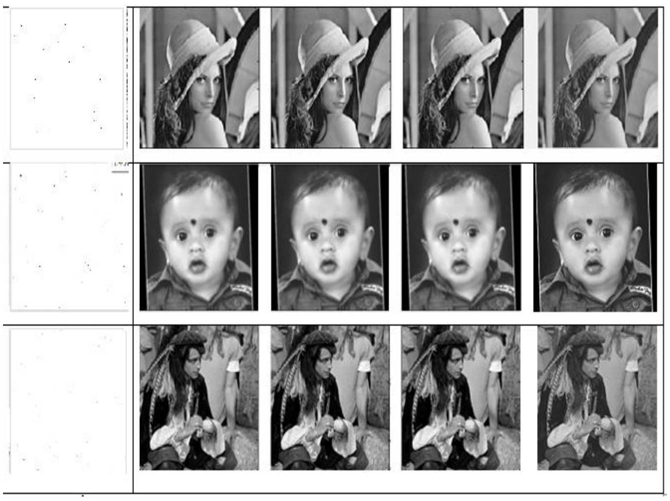

Figure 7 quality comparison for random-value noise removal with the noise level 90%. Column 1: the noisy images; Column 2: the results of KR; Column 3: Cai's results; Column 4: the results of IFASDA; Column 4: regularized regression result results.

For 90% of salt and peppers noise level fig.4 shows the recoverd result of Lena, sai and man. From the results, we observe that at high noise level kernel regression methods generate high frequency components. Result is overblurs by Cai's method, irregular outliers along edges and textures can be causes by IFASDA method, proposed method gives the best quality by combining the intra-scale and inter-scale correlation: using the property of local smoothness image is sharper.

B. Random-Valued Impulse Noise Removal

Now in this, compare performance of restored images that contain only random-value noise. All test images are corrupted by random-value noise with noise level : 80%, 85%. 90%. We use adaptive center weighted median filter to detect random-value noise from image that shown in figure. 7. It is clear that all images in data set gives higher performance of PSNR values as compared with existing methods. For Man, it also shows the effective performance of histogram with compared method that are shown in fig. 8. In the matrix, random-value noise are identically and uniformly distributed. Hence, detection of random-valued impulse noise are more difficult than salt and pepper noise.

As compared to task of salt-and-peppers noise removal ,it is difficult to remove random-valued noise removal task.

For 80% of random-valued impulse noise level, figure 4 shows the recovered result of Lena, sai and man. From the results, here find after noise removal Cai's method and IFASDA still have some regions with noise, such the face region of Lena, the region between Sai face, and the mast region of Man. Proposed method produces more clear results compared with other methods

Table 2 PSNR and TIME quality comparison of images for random-value noise

method	KR		Cai		IFASDA		LAPLACIAN		OUR	
	PSNR	TIME	PSNR	TIME	PSNR	TIME	PSNR	TIME	PSNR	TIME
Lena	27.04	57.25	24.18	547.88	25.12	161.55	28.03	133.92	30.09	120.17
pepper	24.62	57.27	21.76	629.11	22.66	149.41	25.21	134.39	30.26	120.15
Boat	24.89	57.19	21.87	545.98	23.18	148.42	25.57	133.97	30.24	120.09
Man	25.16	57.17	22.29	556.21	23.71	170.86	25.92	133.33	30.31	120.29

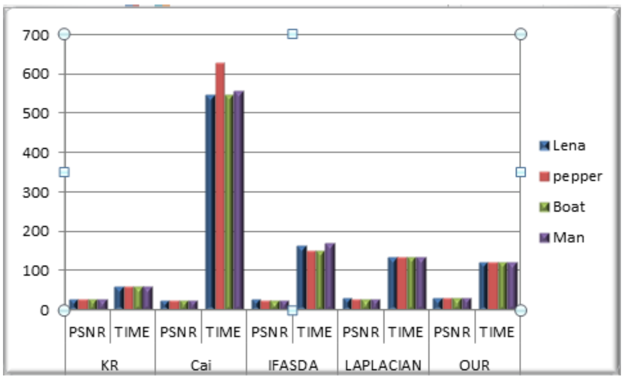

Figure 9 Bar chart for PSNR and TIME quality comparison of algorithms for random-value noise

V RELATED WORK

The new methods and solvers presented in this paper represent just a handful of directions that the generalized functional and solver description Clearly, there are a very large number of other possible methods that can be constructed from the functional components. Here we use tikhonov algorithm for future enhancement that gives the more clear result of PSNR value and TIME as compared to graph laplacian regularized regression.

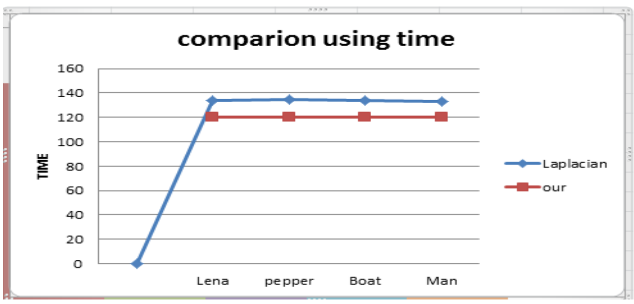

Figure 10 timing comparison between laplacian and proposed method.

VI CONCLUSIONS

In this paper, here present an effective and efficient image impulse noise removal algorithm based on hybrid graph Laplacian regularized regression. We utilize the input space and the mapped high-dimensional feature space as two complementary views to address such an ill-posed inverse problem. The framework we explored is a multi-scale Laplacian pyramid, where the intra-scale relationship can be modeled with the implicit kernel graph Laplacian regularization model in input space, while the inter-scale dependency can be learned and propagated with the explicit kernel extension model in mapped feature space. In this way, both local and nonlocal regularity constrains are exploited to improve the accuracy of noisy image recovery

REFERENCES

[1] M.A.Littel and N.S.Jones,"Generalized methods and solvers for noise removal from piecewise constant signals,"Proc.R.Soc.,Maths.,vol.467,no.2135,pp.3088-31114,2011.

[2] S.-J. Ko and Y. H. Lee, "Center weighted median filters and their applications to image enhancement," *IEEE Trans. Circuits Syst.*, vol. 38,no. 9, pp. 984–993, Sep. 1991.

[3] H. Hwang and R. A. Haddad, "Adaptive median filters: New algorithms and results," *IEEE Trans. Image Process.*, vol. 4, no. 4, pp. 499–502,Apr. 1995.

[4] J. Cai, R. H. Chan, and M. Nikolova, "Fast two-phase image deblurring under impulse noise," *J. Math. Imaging Vis.*, vol. 36, no. 1, pp. 46–53,2010.

[5] W. Hong, J. Wright, K. Huang, and Y. Ma, "Multiscale hybrid linear models for lossy image representation," *IEEE Trans. Image Process.*,vol. 15, no. 12, pp. 3655–3671, Dec. 2006.

[6] S. G. Mallat, *A Wavelet Tour of Signal Processing, the Sparse Way*,3rd ed. Amsterdam, The Netherlands: Elsevier, 2008.

[7] U.chaudhari ,"Image Denoising Using Hybrid Graph Laplacian Regularization "(IJERCSE) Vol. 1, Issue 2, December 2014.