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Image Denoising using Kernel Regression in Real Time Applications

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ABSTRACT: The problem of recovering patterns and structures in images from corrupted observations is encouraged in many engineering and science applications. In many practical image problems observed images often contain noise that should be removed beforehand for improving the visual pleasure and the reliability of image. Images may be contaminated with various types of noise. Among them the impulse noise is one of the most frequently happened noises. So here propose a unified framework to perform progressive image recovery based on hybrid graph laplacian regularized regression. First constructs a multiscale representation of the target image by laplacian pyramid then progressively recovers the degraded image in the scale space from coarse to fine. Within each scale a graph Laplacian regularization model represented by implicit kernel is learned which simultaneously minimizes the least square error on the measured samples and preserves the geometrical structure of the image data space. Between two successive scales the proposed model is extended to a projected high-dimensional feature space through explicit kernel mapping in which the local structure regularity is learned and propagated from coarser to finer. Both local and nonlocal regularity constraints are exploited to improve accuracy of noisy image recovery.

KEYWORDS: Image denoising, graph laplacian, local smoothness, non-local self-similarity, implicit kernel, explicit kernel.

I.INTRODUCTION

Noise means the pixels in the image show different intensity values instead of true pixel values. Noise is a random variations of image Intensity and visible as grains in the image. It may produce at the time of capturing or image transmission. Noise removal algorithm is the process of removing or reducing the noise from the image. The noise removal algorithms reduce or remove the visibility of noise by smoothing the entire image leaving areas near contrast boundaries. There are several ways that noise can be introduced into an image, depending on how the image is created. The performance of an image recovery algorithm largely depends on how well it can employ regularization conditions or priors when numerically solving the problem, because the useful prior statistical knowledge can regulate estimated pixels. Therefore, image modeling lies at the core of image denoising problems. One common prior assumption for natural images is intensity consistency, which means: (1) nearby pixels are likely to have the same or similar intensity values; and (2) pixels on the same structure are likely to have the same or similar intensity values. Note that the first assumption means images are locally smooth, and the second assumption means images have the property of non-local self-similarity. Accordingly, how to choose statistical models that thoroughly explore such two prior knowledge directly determines the performance of image recovery algorithms. Another important characteristic of natural images is that they are comprised of structures at different scales. Through multi-scale decomposition, the structures of images at different scales become better exposed, and hence more easily predicted. At the same time, the availability of multi-scale structures can significantly reduce the dimension of problem hence make the ill-posed problem to be better posed. The multiscale framework provides us a wonderful choice to efficiently combine the principle of local smoothness and non-local similarity for image recovery.

In this method, a multi-scale representation of the target image is constructed by Laplacian pyramid, through which we try to effectively combine local smoothness and non-local self-similarity. On one hand, within each scale, a graph Laplacian regularization model represented by implicit kernel is learned which simultaneously minimizes the least square error on the measured samples and preserves the geometrical structure of the image data space by exploring non-local self-similarity. In this procedure, the intrinsic manifold structure is considered by using both measured and unmeasured samples. On the other hand, between two scales, the proposed model is extended to the parametric manner through explicit kernel mapping to model the interscale correlation, in which the local structure regularity is learned and propagated from coarser to finer scales. Moreover, in our method the objective functions are formulated in the same form for intra-scale and inter-scale processing, but with different solutions obtained in different feature spaces. The solution in the original feature space by implicit kernel is used for intra-scale prediction, and the other solution in a higher feature space mapped by explicit kernel is used for inter-scale prediction. Therefore, the proposed image recovery algorithm actually casts the consistency of local scale scheme into a unified framework.

II.OPTIMIZATION BY IMPLICIT KERNEL

To apply regularized regression first analyzes the nearby pixels which have same or similar intensity values. It is obtained through inter correlation. In order to obtain the optimal solution for the above objective function exploits a useful property called representer theorem. It states that minimizing of any optimization task in Hilbert space *H* has finite representation in *H*. According to the Representer Theorem define *f*(x) as

$$f(x)=\sum_{i=1}^{n} \alpha i k(\mathrm{x}i, \mathrm{x}). \quad (1)$$

Therefore f is defined as

$$\mathrm{f} = \begin{bmatrix} f(\mathrm{x}1) \\ \vdots \\ f(\mathrm{xn}) \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} \alpha i k(\mathrm{x}1, \mathrm{x}i) \\ \vdots \\ \sum_{i=1}^{n} \alpha i k(\mathrm{x}n, \mathrm{x}i) \end{bmatrix} = \mathrm{K}\alpha \quad (2)$$

Where K is the kernel gram matrix

Implicit kernel gives self similarity relation among two same scale images. Through inter correlation implicit kernel is obtained. Denoting K*L* as the submatrix consisting of rows of K corresponding to those labeled samples in the set *XL*.

III.OPTIMIZATION BY EXPLICIT KERNEL

The implicit kernel induced framework addresses the problem of nonlinear estimation in a nonparametric manner, which relies on the data itself to dictate the structure of the model. So further explicitly map samples to a high dimensional feature space in order to reformulate the proposed graph Laplacian regularized model in a linear manner in that space. This will bring additional insights to help addressing the current ill-posed problem.

$$f(x^{\sim})=\sum_{i=1}^{n} \alpha i k(\mathrm{x}i\sim, \mathrm{x}\sim). \quad (3)$$

$$f^{\sim} = \begin{bmatrix} f(\mathrm{x}1\sim) \\ \vdots \\ f(\mathrm{x}n\sim) \end{bmatrix} = \mathrm{X}^{T\sim}\mathrm{w} \quad (4)$$

Hybrid Graph Laplacian Regularization is an effective and efficient image impulse noise removal algorithm as compared with the other methods. The input space and high dimensional feature space is used as two complementary views to address such an ill posed problem. After comparison with other methods it is found that this algorithm achieves the highest PSNR value for all the tested images. In this way both local and nonlocal regularity constrains are exploited to improve the accuracy of noisy image recovery.

IV. PROGRESSIVE HYBRID GRAPH LAPLACIAN REGULARIZATION

A multi-scale representation of the target image is constructed by Laplacian pyramid which efficiently combine local smoothness and non-local self-similarity. Objective functions are the same for intra-scale and inter-scale processing, but with different solutions obtained in different feature spaces. It means the solution on the original feature space by

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implicit kernel is used for intra-scale, and the other solution on the higher feature space mapped by explicit kernel is used for inter-scale. On one hand within each scale a graph Laplacian regularization model represented by implicit kernel is learned which simultaneously minimizes the least square error on the measured samples and preserves the geometrical structure of the image data space by exploring non-local self-similarity. In this procedure the intrinsic manifold structure is considered by using both measured and unmeasured samples. Between two scales the proposed model is extended to the parametric manner through explicit kernel mapping to model the inter-scale correlation in which the local structure regularity is learned and propagated from coarser to finer scales. Hence the proposed method achieves effective image recovery.

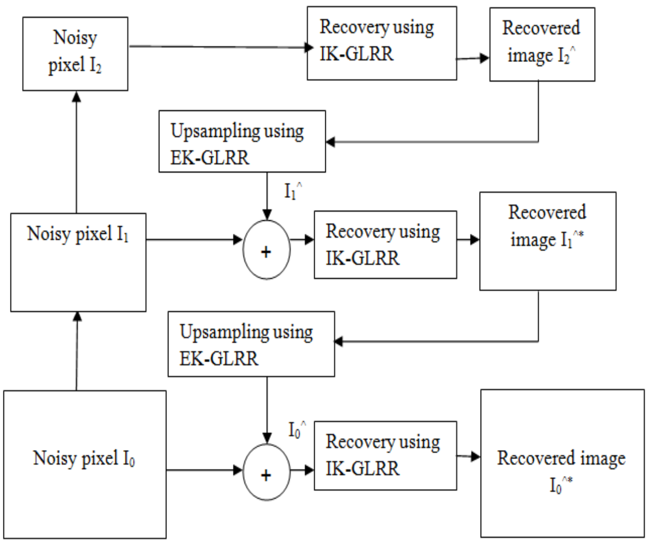

Fig:1 Block diagram of proposed system

Figure shows a multiscale implementation of the hybrid graph Laplacian regularization model. Here 80% samples in the test image peppers are corrupted. The subscript l is used to indicate the level in the pyramid of downsampled images. The finest level is indicated by $l = 0$. The larger is l, the coarser is the downsampled image. The highest level is indicated as $l = L$. The level is increased from 0 to L.0 indicate minimum level and L indicates maximum level.

First, the level l image I_l passes a low-pass filter F, which is implemented in this method by averaging the existing pixels in a 2 × 2 neighborhood on higher resolution. Then the filtered image is downsampled by 2 to get a coarser image I_{l+1}.

$$I_{l+1} = F(I_l) \downarrow 2,\ l = 0, \ldots\ldots, L - 1. \qquad (5)$$

In this way construct a Laplacian pyramid. At the coarsest scale 2, the missing samples in I_2 can be recovered via the proposed IK-GLRR model which has been $I_2^{\wedge}$. And this estimation can be computed iteratively by feeding the processing results$I_2^{\wedge}$ to the estimator as a prior for computing the kernel distance. In practice there are two iterations was found to be effective in improving the processing results in such type of operations. Especially in the first iterations there is only coarsest noisy image I_2. So construct the kernel distance by Gaussian kernel

$$k(x_i, x_j) = exp(\|u_i - u_j\|^2 / \sigma^2) \qquad (6)$$

Where u_i and u_j are the location coordinates of x_i and x_j respectively. The relation between local patches b_i and b_j are centered on x_i and x_j are given by

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$$k(x_i, x_j) = exp(||b_i - b_j||^2 /\sigma^2). \qquad (7)$$

The recovered image $I_2^{\wedge}$ is then upsampled with the proposed kernel EK-GLRR model to get $I_1^{\wedge}$. $I_1^{\wedge}$can be used as a prior estimation for the IK-GLRR model towards a refined estimate $I^{\wedge}{}_1{}^{*}$. $I^{\wedge}{}_1{}^{*}$ can then be upconverted to $I_0^{\wedge}$ by the EK-GLRR model. And the refined estimate $I_0^{\wedge}$ can be combined with I_0 into another IK-GLRR recovery procedure towards the final results $I^{\wedge}{}_0{}^{*}$. Using the above progressive recovery based on intra-scale and inter-scale correlation gradually recover an image with few artifacts.

V. RESULT AND DISCUSSION

It can be clearly observed that the proposed algorithm achieves the best overall visual quality through combining the intra-scale and inter-scale correlation. The image is sharper due to the property of local smoothness preservation when using inter-scale correlation and the edges are more consistent due to the exploration of non-local self-similarity when using intra-scale correlation. This method also achieves the best objective performance among the compared methods. The proposed algorithm achieves the highest average PSNR value for all cases.

Fig 2: input image

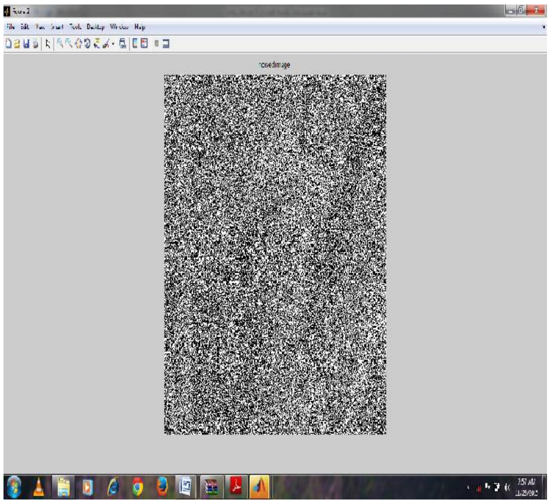

Fig 3: input image with applied impulse noise

Fig 4:output image

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It is clear that the output image is very similar to input image. Also it provides better performance compared to other methods.

VI.CONCLUSION

It is an effective and efficient image impulse noise removal algorithm based on hybrid graph Laplacian regularized regression. It utilizes the input space and the mapped high-dimensional feature space as two complementary views. The framework explored is a multi-scale Laplacian pyramid where the intra-scale relationship can be modelled 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. Experimental results demonstrate graph laplacian regularized regression method outperforms the state-of-the-art methods in both objective and subjective quality. Both local and nonlocal regularity constrains are exploited to improve the accuracy of noisy image recovery. It achieves much better quality with respect to PSNR than other methods and reduces computational complexity. It also capable of restore major edges and repetitive textures of the images. It is noticed that the proposed method can more accurately recover images.

REFERENCES

[1] Gao .W, Liu.X, Ma .S , Sun.H, Xiong .R and Zhao.D. 'Image interpolation via regularized local linear regression,' IEEE Trans. Image Process., vol. 20, no. 12, pp. 3455–3469, 2011.

[2] Hong.W, Huang .K, Ma .Y and Wright.J 'Multiscale hybrid linear models for lossy image representation,' IEEE Trans. Image Process. Vol. 15, No. 12, pp. 3655–3671,2006.

[3] Milanfar.P. 'A tour of modern image filtering,' IEEE Signal Process. Mag., vol. 30, no. 1, pp. 106–128,2013.

[4] Yang .X and Zhai. G. 'Image reconstruction from random samples with multiscale hybrid parametric and nonparametric modeling,' IEEE Trans.Circuits Syst., Vol. 22, No. 11, pp. 1554–1563,2012.

[5] Suman Shrestha 'Image denoising using new adaptive based median filter, An International Journal (SIPIJ) Vol.5, No.4, 2014.

[6] Little.M.A and Jones .N.S. 'Generalized methods and solvers for removal from piecewise constant signals,' Proc. R. Soc., Math.,vol. 467, no. 2135, pp. 3088–3114, 2011.