Color Image Processing

M.Harini[1] P.E.Charanya[2]
[1]Professor [2]Research Scholar (M.Phil)
[1]Department of Computer Applications [2]Department of Computer Science Engineering
[1,2]Sengunthar Arts and Science College, Tiruchengode, Tamil Nadu, India

Abstract— This paper investigates the rrecovering images from corrupted observations is necessary for many real-world applications. In this paper, we propose a unified framework to perform progressive image recovery based on hybrid graph Laplacian regularized regression. We first construct a multiscale representation of the target image by Laplacian pyramid, then progressively recover the degraded image in the scale space from coarse to fine so that the sharp edges and texture can be eventually recovered. The proposed model is extended to a projected high-dimensional feature space through explicit kernel mapping to describe the interscale correlation, in which the local structure regularity is learned and propagated from coarser to finer scales. In this way, the proposed algorithm gradually recovers more and more image details and edges, which could not been recovered in previous scale. We test our algorithm on one typical image recovery task: impulse noise removal.

Key words: Laplacian Regularization, Impulse Noise Removal

I. INTRODUCTION

The problem of recovering patterns and structures in images from corrupted observations is encouraged in many engineering and science applications, ranging from computer vision, consumer electronics to medical imaging. In many practical image processing problems, observed images often contain noise that should be removed beforehand for improving the visual pleasure and the reliability of subsequent image analysis tasks. Images may be contaminated by various types of noise. Images represented in the RGB color model consist of three component images, one for each primary color. When fed into an RGB monitor, these three images combine color image.The number of bits used to represent each pixel in RGB space is called the pixel depth. A color image can be acquired by using three filters, sensitive to red, green, and blue, respectively. When we view color scene with monochrome camera equipped with one of these filters, the result is a monochrome image whoseintensity is proportional to the response of that filter. In this paper, we focus on the task of impulse noise removal.

The non-local self-similarity is based on the observation that image patches tend to repeat themselves in the whole image plane, which in fact reflects the intra-scale correlation. All those findings tell us that local nonlocal redundancy and intra-inter-scale correlation can be thought of as two sides of the same coin. The multiscale framework provides us a wonderful choice to efficiently combine the principle of local smoothness and non-local similarity for image recovery.

II. GRAPH LAPLACIAN REGULARIZED REGRESSION (GLRR)

What we want to derive is the prediction function *f* , which gives the re-estimated values of noisy samples. Given labeled samples Xl = {(x1, y1), . . . , (xl , yl)} as the training data, one direct approach of learning the prediction function f is to minimize the prediction error on the set of labeled samples, which is formulated as follows:

$$\operatorname{argmin}_{f \in H\kappa} J (f) = \operatorname{argmin}_{f \in H\kappa l} \mathrm{sum}_{i=1} \|yi - f (xi)\|^2 + \lambda \|f \|^2,$$

For all xi $\in\chi$, i.e., H_x= span {κ(xi , ·)|xi $\in\chi$}.

The graph Laplacian regularization, the manifold structure can be incorporated in the objective function. Mathematically, the manifold assumption can be implemented by minimizing the following term:

$$R (f) = ½\ \mathrm{sum}^n_{i, j} (f (xi) - f (x j))\ 2Wi\ j.$$

With above representations, the objective function defined and it can be rewritten as:

$$\operatorname{argmin}_{a\in Rn} \{J (a) =\|yl - Kla\|^2 + \lambda a^T Ka + \gamma a^T KLKa\}.$$

By taking ∂ J (a)/∂a = 0, we can derive a closed-form solution as:

$$a* = (KLK^T L + \lambda K + \gamma KLK)^{-1} KLyL.$$

III. SYSTEM MODEL

The IK-GLRR and EK-GLRR models provide two complementary views about the current image recovery task. A natural question is how to combine them together into an elegant framework.

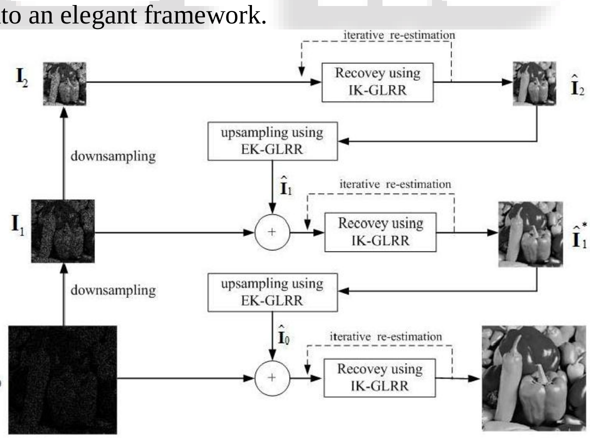


Fig. 1: framework

In this paper, we propose to use a simple multi-scale framework to achieve such a purpose. There are at least several reasons why we use the multi-scale framework. First, one 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 be more easily predicted. Second, a multi-scale scheme will give a more compact representation of imagery data because it encodes low frequency parts and high frequency parts separately. Third, the stronger correlations among adjacent image blocks will be captured in the down sampled images because every four image blocks are merged into one block in the down sampled image. As a consequence, in this paper, we propose an effective approach to recover noisy imagery data by combining hybrid models and the multi-scale paradigm.

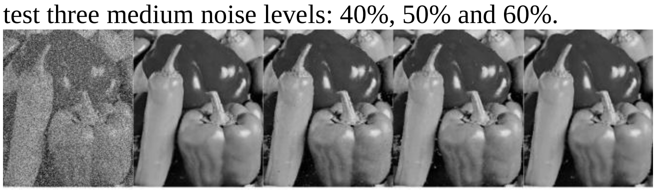
IV. METHODS FOR RESULT ANALYSIS

A. Salt-and-Pepper Noise Removal

We first examine the performance comparison on restoring images contaminated by salt-and-pepper noise only. The test images are corrupted by salt-and-pepper noise with high noise rates: 80%, 85%, and 90%. For detecting salt-and-pepper noise, we use the AM filter with a maximum window size of 19. We quantify the objective performance of all methods by PSNR.The multiscale framework does not work well in this case. In contrast, the single-scale and patch-based kernel regression works better. For images with repetitive structures like *Barbara*, we can degenerate the proposed scheme to single-scale to get better results. 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.

B. Random-Valued Impulse Noise Removal

We now consider the case that test images are corrupted by random-valued impulse noise only. The random noise values are identically and uniformly distributed in [*d*min, *d*max], therefore, clearly random-valued impulse noise are more difficult to detect than salt-and-pepper noise. And the task of random-valued noise removal is expected to be more difficult compared with salt-and-peppers noise removal. Therefore, for random-valued impulse noise removal, we test three medium noise levels: 40%, 50% and 60%.



C. Salt-and-Pepper Noise Removal and Deblurring

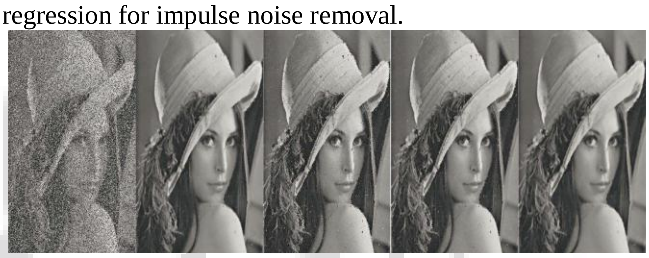
Next, let us examine the performance of compared methods on mixed distortion, that is, performing denoising and deblurring simultaneously, where the test images are first blurred and then added with impulse noise. The blurring operators are Gaussian blur with a window size of 7 × 7 and a standard deviation of 1. We first test salt-and-peppers noise. The added impulse noise is still with three heavy levels: 80%, 85%, 90%.

Our method produces the most visually pleasant results among all comparative studies. Even under blur and impulse noise simultaneously, the proposed algorithm is still capable of restoring major edges and repetitive textures of the images. It is noticed that the proposed method can more accurately recover global object contours.It is easy to find that the edge across the region with heavy noise cannot be well recovered with other methods. This further demonstrates the power of the proposed multi-scale impulse noise removal algorithm. The strength of the proposed progressively recovery approach comes from its full utilization of the intra-scale and inter-scale correlations, which are neglected by the currently available single-scale methods.

D. Random-Valued Noise Removal and Deblurring

We now consider the case that blurred images are corrupted by random-valued impulse noise. We still test three medium noise levels: 40%, 50% and 60%. The proposed method works the best among the compared methods for all test images. The average gain is up to 0.65dB. This demonstrates our method can handle more difficult cases.

The superior subjective and objective qualities of the proposed algorithm convincingly demonstrate the potential of the proposed hybrid graph Laplacian regularized regression for impulse noise removal.



V. CONCLUSION

In this paper, we 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. In this way, both local and nonlocal regularity constrains are exploited to improve the accuracy of noisy image recovery. Experimental results demonstrate our method out performs the state-of-the-art methods in both objective and subjective quality.

REFERENCES

[1] X. Zhu, “Semi-supervised learning literature survey,” Dept. Comput.Sci., Univ. Wisconsin, Madison, WI, USA, Tech. Rep. 1530, 2005.

[2] M. Belkin, P. Niyogi, and V. Sindhwani, “Manifold regularization geometric framework for learning from examples,” J. Mach. Learn.Res., vol. 7, pp. 2399–2434, Nov. 2006.

[3] D. Cai, X. Wang, and X. He, “Probabilistic dyadic data analysiswith local and global consistency,” in Proc. 26th ICML, Jun. 2009,pp. 105–112.

[4] B. Scholkopf, S. Mika, C. J. C. Burges, P. Knirsch, K.-R. Muller,G. Ratsch, et al., “Input space versus feature

space in kernel-basedmethods," IEEE Trans. Neural Netw., vol. 10, no. 5, pp. 1000–1017,May 1999.
[5] D. Zhai, X. Liu, D. Zhao, H. Chang, and W. Gao, "Progressiveimage restoration through hybrid graph Laplacian regularization," in Proc. IEEE Data Compress. Conf., Snowbird, UT, USA, Mar. 2013,pp. 103–112.
[6] H. Takeda, S. Farsiu, and P. Milanfar, "Kernel regression for imageprocessing and reconstruction," IEEE. Trans. Image Process.vol 16no. 2, pp. 349–366, Feb. 2007.
[7] Gonzalez, R.C. and R.E. Woods, Digital image processing, Pearson Education",2002.
[8] R. H. Chan, C. Hu, and M. Nikolova, "An iterative procedu, forremoving random-valued impulse noise," IEEE Signal Process. Lett.,0vol. 11, no. 12, pp. 921–924, Dec. 2004.
[9] P. Milanfar, "A tour of modern image filtering," IEEE Signal Process.Mag., vol. 30, no. 1, pp. 106–128, Jan. 2013.
[10] Haralick R. and Shaprio L., "Image segmentation techniques," Computer vision ,Graphics and image processing, vol., 29, no. 1, pp.100-132,1985.

