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Article Title: Lifting Inspired Invertible Sparsity Driven Denoising Networks

Lifting Inspired Invertible Sparsity Driven Denoising Networks

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ABSTRACT

Image denoising aims to restore a clean image from an observed noisy one. Model based image denoising approaches can achieve good generalization ability over different noise levels and are with high interpretability. Learning-based approaches are able to achieve better results, but usually with weaker generalization ability and interpretability. In this paper, we pro pose a wavelet-inspired invertible network (WINNet) to combine the merits of the wavelet-based approaches and learning based approaches. The proposed WINNet consists of K-scale of lifting inspired invertible neural networks (LINNs) and sparsity-driven denoising networks together with a noise estimation network. The network architecture of LINNs is inspired by the lifting scheme in wavelets. LINNs are used to learn a non-linear redundant transform with perfect reconstruction property to facilitate noise removal. The denoising network implements a sparse coding process for denoising. The noise estimation network estimates the noise level from the input image which will be used to adaptively adjust the soft-thresholds in LINNs. The forward transform of LINNs produces a redundant multi-scale representation for denoising. The denoised image is reconstructed using the inverse transform of LINNs with the denoised detail channels and the original coarse channel. The simulation results show that the proposed WINNet method is highly interpretable and has strong generalization ability to unseen noise levels.

Keywords: Image Denoising; Wavelet-Inspired Invertible Network; Lifting inspired invertible neural networks; wavelets; Etc.

1 Introduction

Image denoising is a classical and fundamental inverse problem in image processing and computer vision. Image denoising algorithms aim to restore a noiseless image from noisy observations obtained by digital cameras. Given that the observations are inevitably noisy due to the random nature of the photon emission and sensing process, and the imperfection of the signal conversion process, image denoising is an essential step for further image processing and computer vision applications. With the plug-and-play and the unfolding technique, image denoising algorithms have become even more important as they can also be used to solve other image restoration problems by acting as a powerful prior. In this paper, I assume the noise is additive, white and Gaussian. The model-based methods use optimization strategies based on well-defined image priors or noise statistics which lead to algorithms with good interpretability and strong generalization ability. The typical priors used for image denoising include for instance image-domain smoothness, transform-domain sparsity patch-domain non-local self-similarity. The wavelet transform has been very effective in many imaging applications. It provides a versatile multi-resolution analysis with perfect reconstruction property and time-

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pp. 80-88

frequency localization property. Therefore, the wavelet transform has been applied for a wide range of image restoration problems, including image denoising image deconvolution and image in painting. The wavelet transform is a fixed transform and, in some cases, learning a transformation better adapted to the data at hand may lead to more effective solutions. Dictionary learning tries to achieve that by learning a (redundant) sparsifying transform from training data. However, both the analytical transforms and the learned dictionaries are linear transformations. A suitable non-linear transform with perfect reconstruction property has the potential to achieve better performances.

The overall network structure follows the principles of wavelet thresholding and consists of a multi-scale forward transform, denoising of the detail coefficients, and inverse transform. However, instead of using fixed and linear transform, I propose to learn a non-linear transform based on the lifting scheme. In the design I want the non-linear transform to inherit the sparsifying ability, perfect reconstruction property as well as the multi-scale property of the wavelet transform. Here I propose a novel wavelet-inspired invertible network (WINNet) with redundant invertible sparsifying transforms by leveraging the invertible neural network framework. By following a strategy similar to wavelet domain thresholding, I aim to enhance the generalization ability and interpretability of the learning-based image denoising method. I propose to learn a non-linear wavelet-like transform with perfect reconstruction (PR) property using invertible neural networks with a structure inspired by the lifting scheme rather than learning features with unconstrained CNNs. I call these lifting inspired networks LINNs. The proposed WINNet is made of several LINNs, one per scale. With PR property, each learned LINN can serve as a versatile transform which can transform the input image to sparse transform coefficients using its forward pass and then inversely transform the denoised coefficients back to image domain using its backward pass. For denoising of transform coefficients, a sparsity-driven denoising network is applied to remove the noise. Moreover, to achieve good generalization ability, all the soft-thresholds in WINNet are set to be noise adaptive and can be adjusted according to the estimated noise level. In this way, the proposed denoising network achieves good generalization ability even to unseen noise. The noise level is estimated using a model-inspired noise estimation network which exploits low-rank patches on the input noisy image and estimates noise levels as the minimum singular value of the weighted patches.

OBJECTIVES

- Reduce computational complexity
- Improve the accuracy
- Achieve blind image denoising.
- Ability to unseen noise levels.
- Improve the training memory and runtime consumption

2 Related Work

Removal of noise from an image is an extensively studied problem in image processing. Indeed, the recent advent of sophisticated and highly effective denoising algorithms lead some to believe that existing methods are touching the ceiling in terms of noise removal performance. Can I leverage this impressive achievement to treat other tasks in image processing? Recent work has answered this question positively, in the form of the Plug-and-Play Prior (P3) method, showing that any inverse problem can be handled by sequentially applying image denoising steps. This relies heavily on the ADMM optimization technique in order to obtain this chained denoising interpretation. Is this the only way in which tasks in image processing can exploit the image denoising engine? In this paper I provide an alternative, more powerful and more flexible framework for achieving the same goal. As opposed to the P 3 method, I offer Regularization by Denoising (RED): using the denoising engine in defining the regularization of the inverse problem. I propose an explicit image-adaptive Laplacian-based regularization functional, making the overall objective functional clearer and better defined. With a complete flexibility to choose the iterative optimization procedure for minimizing the above functional, RED is capable of incorporating any image denoising algorithm, treat general inverse problems very effectively, and is guaranteed to converge to the globally optimal result. I test this approach and demonstrate state-of-the-art results in the image deblurring and super-resolution problems.

The lifting inspired invertible neural network (LINN) is used to replace one level of the wavelet transform. Compared to wavelet transforms and learned dictionaries, LINN can represent more complex features. Similar to the lifting scheme which splits the input signal and then alternates prediction and update, LINN consists of splitting/merging operators and learnable predict and update networks. Since LINN satisfies PR conditions, the obtained transform coefficients contain the same amount of information as the input image. Though noise is not removed in the transform coefficients, the non-linear transform will learn to separate signal and noise into the coarse and detail parts through the denoising operation applied on the detail part. The PR property of LINN also makes it a versatile transform for image denoising with different noise levels and for other image restoration problems. The splitting operator is used to separate the input image into two parts in the forward pass of LINNs, and the merging operator performs the inverse of the splitting operator in the backward pass of LINNs. At each scale, the Predict/Update networks are shared among the forward and inverse transform of LINN, but are connected with different signs and directions. To select low-rank patches from the input noisy image and estimate the noise level as the smallest eigenvalue of the covariance matrix of the selected low-rank patches. A depth-wise separable convolution layer consists of a depth-wise convolution layer and a 1×1 convolution layer. Multi-resolution signal decomposition is an essential property of the wavelet transform. For an input image, the wavelet transform provides a multi-scale analysis which captures the information at different scales. For images with larger noise levels, the soft-thresholds will be larger leading to more effective denoising.

2.1 Image Processing System

Image Processing deals with the processing and display of images of real objects. Their emphasis is on the modification of the image, which takes in a digital image and produces some other information, decision etc. A digital image is an array of real or complex processing of any two dimensional data.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 80-88

The elements of the general-purpose system capable of performing the image processing operations are:

Image Acquisition: Image acquisition is the process of acquiring the digital images using some physical devices and digitizer. The most commonly used image acquisition devices are scanner and video cameras.

Image Storage: Storage of digital processing elements falls in the following three categories. They are

- Short-term storage - used during processing
- Online storage - for relatively fast recall
- Archival storage - characterized by infrequent access

Processing The Image: Processing of digital image involves procedures that are usually expressed in algorithmic form. The exception of image acquisition and display, most image processing functions implemented in software.

Communication: Communication in digital image primarily involves local communication between image processing systems and remote processing systems and remote communication from one point to another, typically in connection with the transmission of image hardware.

Display: After all processing are done, the image will be displayed.

Steps in Image Processing

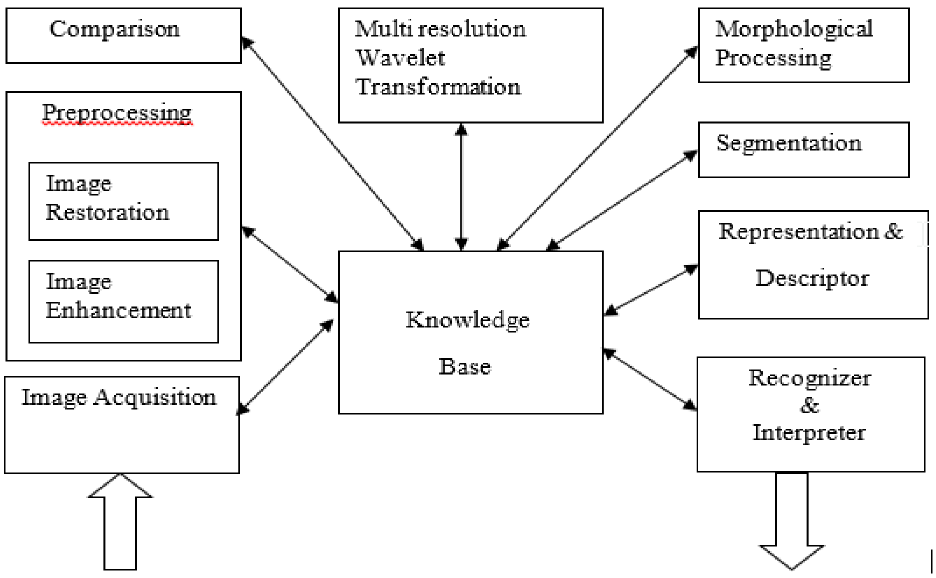

Figure1: *Steps in Image Processing*

System Modules

- Input Image
- Pre Processing
  - Resize image
  - Histogram Equalization
- Splitting Patches Image

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 80-88

- LINN Denoise Network
- Compare PSNR Value

3 Module Description

Data Set Image: The learning-based methods construct a denoising model by learning from noisy-clean image pairs. The flexibility of deep network structure design and the availability of large training dataset and high computational resources boosts the performance, while the learned models have more restricted generalization ability compared to the model-based methods and are usually treated as black-box systems. Therefore, researchers mainly aim to explore learning-based methods with more efficient and effective architecture as well as strategies to improve the generalization ability of the learned denoising model.

Pre-processing: Images acquired for different experiments from the digital camera are cropped, resized and transformed into gray image. The following preprocessing filtering methods are used to remove the noise and enhance the image for restoration.

Splitting Patches Layer Image: The split operator with a redundant linear operator which leads to a redundant decomposition. In the backward pass of LINNs, the merge operator is the corresponding inverse of the split operator. Moreover, at larger scales besides leading to an effective and versatile non-linear invertible transform, this approach also leads to a very effective denoising algorithm. Similar to the lifting scheme which splits the input signal and then alternates prediction and update LINN consists of splitting/merging operators and learnable predict and update networks.

$$\boldsymbol{F}^k = \boldsymbol{K}_{\mathcal{S}} \otimes \boldsymbol{Y}^k,$$

PSNR (peak signal to noise ratio): The signal-to-noise ratio (SNR) is the ratio of the signal power to the noise power in a captured image signal. SNR stated as

$$\mathrm{SNR} == 10\log_{10}\left(\frac{\mathrm{P_s}}{\mathrm{P_n}}\right)^2 = 10\log_{10}\left(\frac{\mathrm{A_{signal}}}{\mathrm{A_{noise}}}\right)^2$$

The splitting operator is used to separate the input image into two parts in the forward pass of LINNs, and the merging operator performs the inverse of the splitting operator in the backward pass of LINNs. The splitting/merging operators in current methods act as a non-redundant transform and keep the same number of input and output coefficients.

Lifting Inspired Invertible Neural Networks: The lifting inspired invertible neural network (LINN) is used to replace one level of the wavelet transform. Compared to wavelet transforms and learned dictionaries, LINN can represent more complex features. Similar to the lifting scheme which splits the input signal and then alternates prediction and update LINN consists of splitting/merging operators and learnable predict and update networks.

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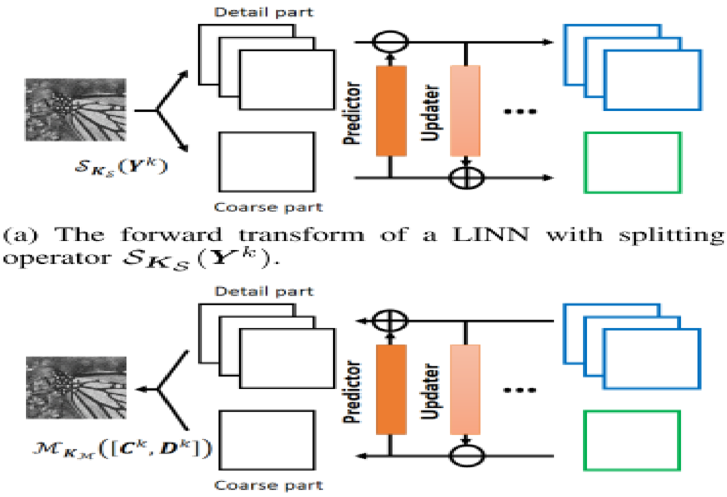

Figure 2: *The forward transform and the inverse transform of a LINN*

The performance of the approach is shown in the figure which is diagrammatically represented as follows;

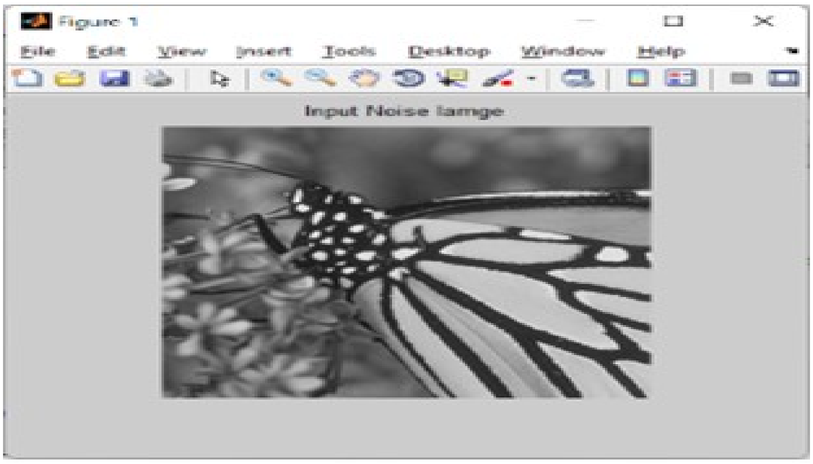

Figure 3: *Input image*

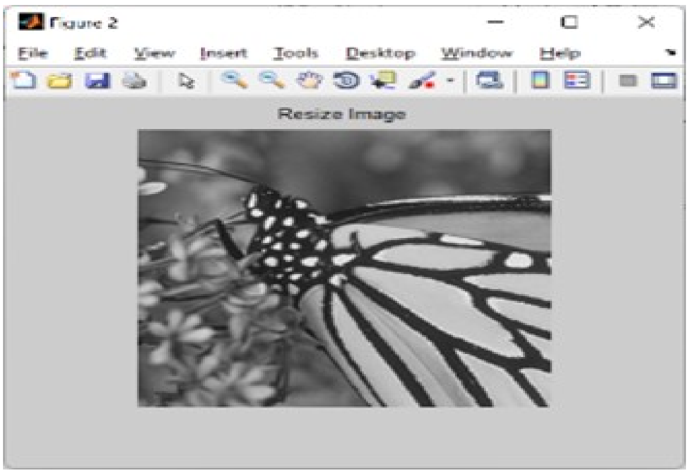

Figure 4: *Resize image*

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pp. 80-88

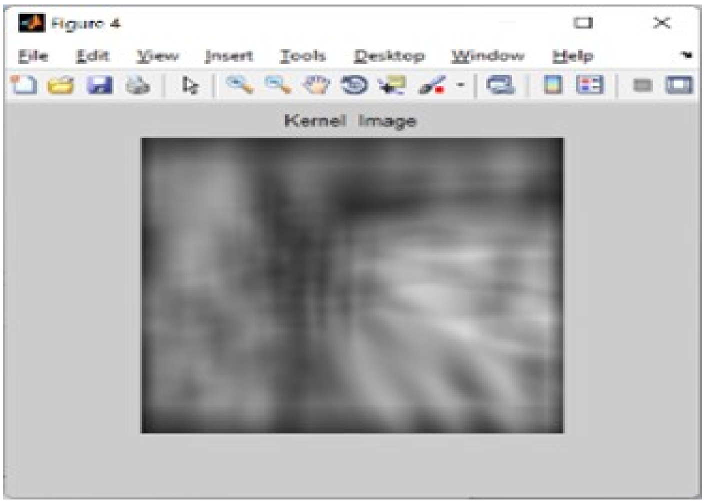

Figure 5: *Kernal Matrix image*

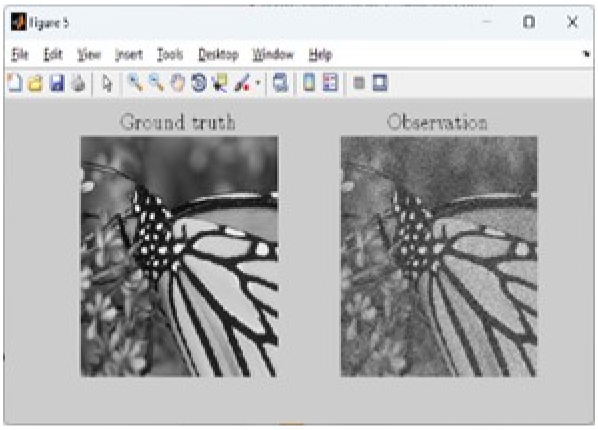

Figure 6: *Ground Truth Lift Network Using Merge Image*

Figure 7: *Final Denoise Output using LINN*

4 Future Scope And Conclusion

In this paper, I have proposed a wavelet-inspired invertible network (WINNet). It consists of K levels of lifting inspired invertible neural network (LINN) and sparsity-driven denoising

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pp. 80-88

networks. LINNs are designed to mimic the nice properties of wavelet transform and are used as a non-linear redundant transform with perfect reconstruction property. For image denoising task, the sparsity-driven denoising network is used to remove the noise in the detail parts of the transform coefficients and the denoising network can be adjusted to adapt to unseen noise levels. Together with a model-inspired noise estimation network, the proposed blind WINNet can achieve robust blind image denoising results beyond the training noise levels. The flexibility of WINNet has also been demonstrated on the image deblurring task. WINNet as a learnable transform-based image restoration method can be exploited as building block in other deep neural network based image processing tasks to enhance the model interpretability and impose reconstruction constraint on the solutions. It would also be interesting to investigate the non-linear image approximation properties of WINNet. Another direction is to improve the training memory and runtime consumption of WINNet.

In the future, WINNet as a learnable transform-based image restoration method can be exploited as building block in other deep neural network based image processing tasks to enhance the model interpretability and impose reconstruction constraint on the solutions. It would also be interesting to investigate the non-linear image approximation properties of WINNet. Image Restoration (IR) consists of a family of ill-posed inverse problems which have been studied extensively through the lens of model and learning-based methods.

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