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Image De-Noising Based on Block Diagonal Representation

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Abstract: - IMAGE de-noising plays an important role in modern image processing systems. Image Filtering is challenging in terms of both efficiency and effectiveness. Patch similarity is major concern in filtering. By grouping similar patches to utilize the self-similarity and sparse linear approximation of natural images, recent nonlocal and transform domain methods have been widely used in colour image de-noising. The importance of the patch level representation is understated. In this paper, we mainly investigate the influence and potential of representation at patch level by considering a general formulation with block diagonal matrix. We further show that by training a proper global patch basis, along with a local principal component analysis transform in the grouping dimension, a simple transform-threshold-inverse method could produce very competitive results.

Key Words: — Filtering, block diagonal matrix, Patch, Principal component analysis, Threshold inverse method.

I. Introduction

Image de-noising is used to remove the additive noise while retaining as much as possible the important signal features. Generally, data sets collected by image sensors are contaminated by noise. Imperfect instruments, problems with data acquisition process, and interfering natural phenomena can all corrupt the data of interest. Thus noise reduction is an important technology in Image Analysis and the first step to be taken before images are analyzed. Therefore, Image De-noising techniques plays important role in image processing [1] Most of the existing de-noising algorithms are developed for grayscale images. It is not trivial to extend them for colour image de-noising since the noise statistics in R, G, and B channels can be very different for real noisy images.

In addition to the design of de-noising strategy, noise modeling is also important. Most of existing methods consider additive white Gaussian noise (AWGN) and some efficient noise estimation methods [22], [20] can be employed. Besides, some non-Gaussian de-noises are proposed for filtering Position noise [21], mixed Gaussian and impulsive noise [15] and stripe noise [16]. In fact, noise in real-world images may be multiplicative and signal dependent [16], making noise modelling and estimation much more complex and challenging. and consider the non-linear processing steps in the camera pipeline in the noise model, and combine external and internal priors. Some methods, including the well-known software toolbox Neat Image (NI) are developed for noise reduction of real-world images. Apart from the conventional transform-domain approaches, many recent competitive methods are based on the advent of deep learning technique as a powerful feature extraction tool. Many competitive methods [13], [15], [21] attempt to approach the optimal performance by modeling the redundancy and correlation at group level with some iterative strategies and a large number of similar patches. However, influence of the patch level representation is less carefully studied. Although the use of tensor representation may help preserve some structure information, the straightforward folding and unfolding operation may not fully exploit the relationship among all channels or spectral bands. The potential and influence of patch level representation, and establish a general formulation with block diagonal matrix.

At present many de-noising approaches are applied in the images to remove noise. However, different colour prior knowledge often has its own scene limitation. We investigate the influence and potential of representation at patch level by considering a general formulation with block diagonal matrix. We further show that by training a proper global patch basis, along with a local principal component analysis transform in the grouping dimension, a simple transform-threshold-inverse method [2] could produce very competitive results. Fast implementation is also developed to reduce computational complexity. Extensive experiments on both simulated and real datasets demonstrate its robustness, effectiveness and efficiency.

II. METHODOLOGY

A. Image De-Noising

The purpose of image processing is divided into 5 groups. They are visualization Observe the objects that are not visible. Image sharpening and restoration to create a better image. Image retrieval – seek for the image of interest. Measurement of pattern – measures various objects in an image. Image recognition – distinguish the objects in an image. Digital image processing deals with manipulation of digital images through a digital computer. The input of that system is a digital image and the system process that image using efficient algorithms, and gives an image as an output.

An image is often corrupted by noise in its acquisition and transmission. Image de-noising is used to remove the additive noise while retaining as much as possible the important signal features. Generally, data sets collected by image sensors are contaminated by noise. Imperfect instruments, problems with data acquisition process, and interfering natural phenomena can all corrupt the data of interest. Thus noise reduction is an important technology in Image Analysis and the first step to be taken before images are analyzed. Therefore, Image De-noising techniques are necessary to prevent this type of corruption from digital images. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise is observed in ultrasound images.

Different noise sources like dark current noise introduced different types of noises. Dark current noise usually presents due to the thermally generated electrons at sensor sites. It is proportional to the exposure time and highly dependent on the sensor temperature. Shot noise which follows a Poisson distribution, is due to the quantum uncertainty in photoelectron generation. Amplifier noise and quantization noise arises when number of electrons converts into pixel intensities. Thus, de-noising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient de-noising technique to compensate for such data corruption. Spatial filters like mean and median filter are used to remove the noise from image. But the disadvantage of spatial filters is that these filters not only smooth the data to reduce noise but also blur edges in image. Therefore, Wavelet Transform is used to preserve the edges of image. There are three basic approaches to image de-noising – Spatial Filtering, Transform Domain Filtering and Wavelet Thresholding Method [5]. Objectives of any filtering approach are: To suppress the noise effectively in uniform regions, to preserve edges and other similar image characteristics, to provide a visually natural appearance.

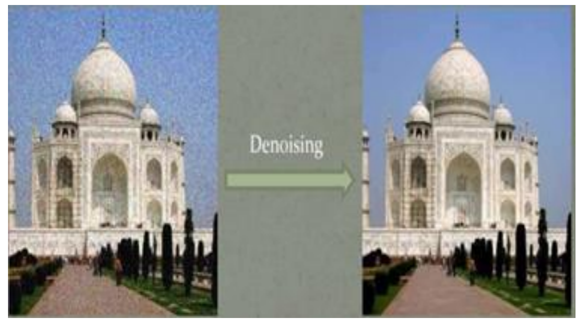

Figure.1. Image De-noising

B. Implementation

The noise in standard RGB space could be approximately modelled as block diagonal representation. Using a 4D transform for CBM3D may be a little confusing, because after a certain colour space transform, the original R, G, B channels are computed separately in the new colour space, which also holds for 4DHOSVD if all mode transforms are obtained. Therefore, it may be re-formulate as independent channel-wise (third-order tensor) transform. So first generalize patch level representation via block diagonal matrix, then select the proper choice for patch-level basis, and implement how it could be properly incorporated into the block diagonal representation and efficiently applied to image de-noising.

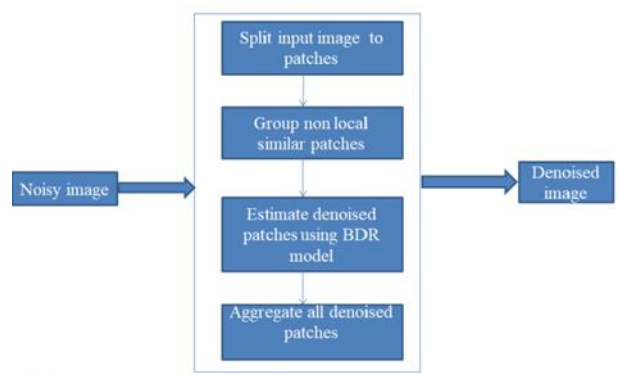

Figure. 2. System architecture

C. Framework:

There are 3 steps to build the de-noisy image. Trained images are applied to this framework.

Grouping:

A reference patch Pref is taken from the trained group and calculate its Euclidean distance with all patches located in the search window. Stack these distances to K most similar patches in the group.

Collaborative filtering:

A fourth mode tensor group is learning from the group via full PCA and obtains the core tensor in the Fourier domain. Apply hard threshold technique and then a filtered group is obtained by multiplying core tensor with patch representation group.

Aggregation:

Averagely write back all image patches in group to their original locations

D. Block diagonal Representation (BDR Model)

The image is applied to framework and the BDR method implemented to remove noise. Tensor notation [10] is used. Tensor is a multidimensional array, also known as a multi way array, and its order is defined as the number of its dimension. Specifically, given a reference patch Pref, the grouping step stacks some similar overlapping patches located in a local window SR into a group represented by matrix G or higher order tensor G with certain matching criteria. One simple and commonly adopted metric is Euclidean distance. Collaborative filtering is then performed on group **G** to utilize the nonlocal similarity feature and estimate clean underlying patches from noisy observation, and it can be generally formulated as:

$$\hat{G} = \arg\min \| G - G \|_{2F} + \rho \cdot \Psi(Gc) Gc \qquad (1)$$

where Gn and Gc are noisy and underlying clean group of patches, respectively, $\|Gn - Gc\|_2$ measures the conformity between Gc and Gn, and Ψ(Gc) represents certain priors. The state-of-the-art BM3D and HOSVD algorithms attempt to model sparsity in the transform domain by shrinking coefficients T (Gn) under a pre-defined threshold τ via

$$T(Ght) = T(Gn), |T(Gn)| \geq \tau$$

$$=0, \ |T(Gn)| < \tau \qquad (2)$$

Some representative techniques and priors are listed in Table I. After collaborative filtering, the estimated clean patches are averagely written back to their original location to further smooth out noise. More specifically, every pixel p̂i of the de-noised image is the (weighted) average of all pixels at the same position of filtered group Ĝ, which can be formulated as

$$\hat{p}i = \sum wik \ \hat{p}ik \ \hat{p}ik \pounds \hat{G} \qquad (3)$$

Where wik and ^pik denote weight and pixel, respectively. The patch level grouping is represented as block diagonal matrix.

$$bdiag(Pi) = \begin{pmatrix} Pi(:;:;1) & & \\ & Pi(:;:;2) & \\ & & Pi(:;:;3) \end{pmatrix} \qquad (4)$$

Where each matrix on the diagonal position is a linear combination of all frontal slices of Pi via

$$Pi(:,:,k) = \sum_{j=0}^{3} Ucolor(j,k) Pi(:,:,j), k = 1,2,3 \qquad (5)$$

$$fdiag(G) = \begin{pmatrix} gi(:,1,:,:) & & \\ & gi(:,2,:,:) & \\ & & gi(:,3,:,:) \end{pmatrix} \qquad (6)$$

$$c = fdiag(G) \times 1bdiag(UTrow) \times 2bdiag(UTcol) \times 3UTgroup \qquad (7)$$

To denote bdiag(Urow) and bdiag(Ucol) as

$$bdiag(U) = \begin{pmatrix} U & & \\ & U & \\ & & U \end{pmatrix} \qquad (8)$$

A suitable alternative to utilizing more group level information (grouping more patches), is the recursive use of patch-level correlation via block circular representation (BCR)

$$bcir(pi) = \begin{pmatrix} pi(:,:,1) & pi(:,:,3) & pi(:,:,2) \\ pi(:,:,2) & pi(:,:,1) & pi(:,:,3) \\ pi(:,:,3) & pi(:,:,2) & pi(:,:,1) \end{pmatrix} \qquad (9)$$

Tensor Decomposition in the Fourier Domain is calculated and grouping is performed.

III. ALGORITHM

Input: Color, patch size ps, local search window size SR, number of similar patches K, pixels between two adjacent reference patches $N_{step.}$

Output: Filtered image Ac.

- Train the global patch representation of row and column with all reference patches using the nonlocal tensor value.
- Grouping the reference patches
- Calculate Euclidean distance with all patches in search window
- Stack similar patches in a group G
- Collaborative filtering
  1. Find factor matrix of group G via PCA in Fourier tensor matrix.
  2. Apply the hard-threshold technique to core tensor matrix from the above result.
  3. In the Fourier domain, whose elements smaller than a certain threshold is set to zero.
  4. Obtain filtered group.
- Aggregate the image patches averagely write back all image patches in to their original locations.

IV. PARAMETERS

A. PSNR

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs. The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality.

B. SSIM

Structural Similarity Index Measure is used for image quality assessment.it is a metric for measuring similarity of two images. It is based on human visual system. It measures perceptual difference between two images.

V. RESULTS AND DISCUSSION

The image dataset is applied to the input and de-noised image is displayed with parameter values. User can upload the image in two ways. First, images upload from the computer gallery and second are to capturing real time image from the camera. The de-noise system processes the image and get image without noise.

The noisy image will have processed by splitting it into patches and then group the similar patches of the image. The groups are filtered by collaborative filtering method. Then the filtered groups are joined together to form de-noisy image. The grouping of patches is done through threshold method and obtains a tensor matrix. The de-noised image will remove almost all noises from the image.

These proposed method shows that the better output can be achieved compared to all other technique, which does not take much computational time as other, these seems to be the another advantage of this method. This has been illustrated with the help of other simulation results. Each image takes different number of iterations based on the amount of noise present in it. Thus by using the proposed technique can greatly reduce the noise in short time. The computational complexity is also very low and reduced computational time.

Figure.3. Loading Image and adding Noise

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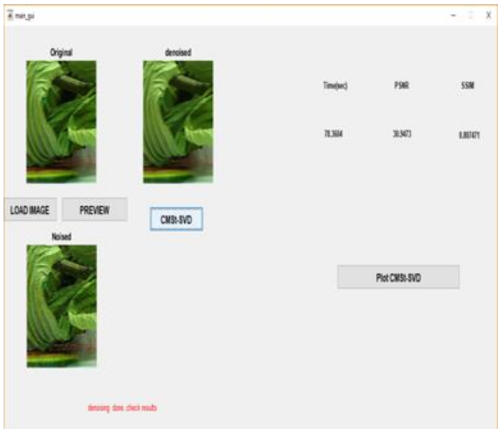

Figure.4. De-noised Image

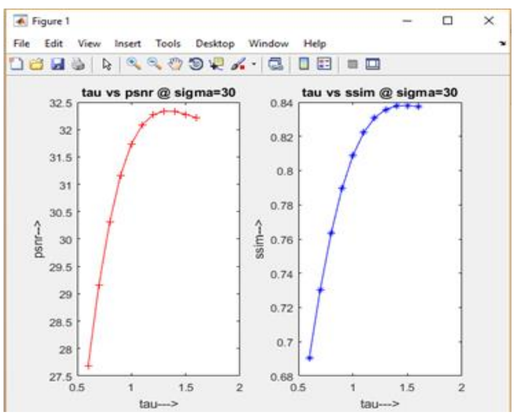

Figure.5. Plotting of Parameters

VI. CONCLUSION

An image is often corrupted by noise during its acquisition and transmission. The real noisy colour images have different noise statistics across the R, G, B channels due to digital camera pipelines in CCD or CMOS sensors. This makes the real colour image de-noising problem more challenging than grayscale image de-noising. In this paper, we proposed a block diagonal de-noising model to effectively exploit the redundancy across colour channels while differentiating their different noise statistics. We implemented a tensor and threshold method in BDR model and PCA transform is applied. The proposed algorithm produces competitive performance with filters in terms of both efficiency and effectiveness. Thus by using the proposed technique can greatly reduce the noise in short time. The computational complexity is also very low and reduced computational time. The future research also includes classification and related image restoration problems and model can be extended for hyper spectral image analysis, which may contain hundreds of bands with complex noise statistics.

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