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Performance Evaluation Of A Modified Method Based On Patch Based Image Modelling For Image Denoising

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Abstract: Digital images play a significant role both in daily life as well as in areas of research and technology. Data sets collected by image sensors are generally infected by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising process is often a necessary and the first step to being taken before the images data is being analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. The challenge of any image denoising algorithm is to suppress noise while producing sharp images without loss of finer details. A modified method based on patch-based image modeling is proposed in this research work. The main part of proposed method is the use of image nonlocal self-similarity (NSS) prior. NSS prior refers to the fact that a local patch often has many nonlocal similar patches to it across the image. This fact significantly enhances the denoising performance. Patch Groups are extracted from training images by putting nonlocal similar patches into groups. According to these Patch Groups, Gaussian Mixture Model learning algorithm is developed to learn the NSS prior. The whole process is repeated 4 times to make the system learn more and more. The iteration process regulates and optimized some of the variables. MSE (Mean Square Error), PSNR (Peak Signal to Noise Ratio) and Correlation coefficient has been taken as output parameters to evaluate the performance of proposed system. MATLAB R2013a has been taken as implementation platform using image processing toolbox.

Keywords: Denoising, Filtering, Image, Noise Models, Review, Spatial Domain, Transform Domain.

INTRODUCTION

Data sets collected by image sensors are generally contaminated by noise [6]. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to being taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images [1].

Using multi-view images for noise reduction has a unique advantage: pixel correspondence from one image to all other images is determined by its single depth map. This advantage contrasts with video denoising, where motion between frames, in general, has many more degrees of freedom [4].

As a classical problem in low-level vision, image denoising has been extensively studied, yet it is still an active topic for that it provides an ideal test bed for image modeling techniques. In general, image denoising aims to recover the clean image x from its noisy observation $y = x + v$, where v is assumed to be additive white Gaussian noise [2].

DENOISING METHODS

Denoising is the process of removing or reducing the inherent noise from a given image. There are numerous techniques available for this purpose. The selection of the denoising technique depends on the type of image & the noise model present in that image. The denoising of the image can be done in two ways: linear filtering and nonlinear filtering. In the case of linear filtering, the noise reduction algorithm is applied to all pixels of the image linearly without knowing about noisy pixel and non-noisy pixel whereas the nonlinear filters are applied on pixels surrounded by the noisy pixels [5]. There are two fundamental approaches to image denoising:

Spatial domain filtering

Transform-domain filtering

Spatial domain Filtering

Spatial domain methods also called spatial filters, estimate each pixel of the image by performing a weighted average of its local/nonlocal neighbors, in which the weights can be determined by their similarities and higher weights are given to similar pixels. Therefore, spatial filters can be further divided into local filters and nonlocal filters [7].

Transform Domain Filtering

Transform domain methods assume that the image can be sparsely represented by some representation basis, such as wavelet basis and its directional extensions. Due to the sparsity of representation coefficients, noise is uniformly spread throughout the coefficients in the transform domain, while most of the image information is concentrated on the few largest ones.

Patch Group Based Prior Modeling of Nonlocal Self-Similarity

Image nonlocal self-similarity (NSS) has been widely adopted in patch-based image denoising and other image restoration tasks. Despite the great success of NSS in image restoration, most of the existing works exploit the NSS only from the degraded image. Usually, for a given patch in the degraded image, its nonlocal similar patches are collected, and then the nonlocal means or 3D transforms or some regularization terms can be introduced for image restoration. However, how to learn the NSS prior from clean natural images and apply it to image restoration is still an open problem. In this work, we make the first attempt on this problem and develop a patch group (PG) based NSS prior learning scheme [3].

IMAGE DENOISING BY PATCH GROUP PRIORS

Denoising Model

Given a noisy image y , like in the PG-GMM learning stage, for each local patch we search for its similar patches in a window centered on it to form a PG, denoted by $Y = (y_1, \dots, y_m)$. Then the group means of Y , denoted by μ_y , is calculated and subtracted from each patch, leading to the mean subtracted PG \bar{Y} [3].

We can write \bar{Y} as $\bar{Y} = \bar{X} + V$, where \bar{X} is the corresponding clean PG and V contains the corrupted noise. The problem then turns to how to recover \bar{X} from \bar{Y} by using the learned PG-GMM priors. Note that the mean μ_y of \bar{Y} is very close to the mean of \bar{X} since the mean vector of noise V is nearly zero. μ_y will be added back to the denoised PG to obtain the denoised image.

GAUSSIAN COMPONENT SELECTION

For each \bar{Y} , we select the most suitable Gaussian component to it from the trained PG-GMM. We suppose that the variance of Gaussian white noise corrupted in the image is σ^2 , the covariance matrix of the k th component will become $\Sigma_k + \sigma^2 I$, where I is the identity matrix. The selection can be done by checking the posterior probability that \bar{Y} belongs to the k th Gaussian component:

$$P(k|\bar{Y}) = \frac{\prod_{m=1}^M \mathcal{N}(\bar{y}_m | \mathbf{0}, \Sigma_k + \sigma^2 \mathbf{I})}{\sum_{l=1}^K \prod_{m=1}^M \mathcal{N}(\bar{y}_m | \mathbf{0}, \Sigma_l + \sigma^2 \mathbf{I})} \quad (1)$$

Taking log-likelihood of (1), we have

$$\ln P(k|\bar{Y}) = \sum_{m=1}^M \ln \mathcal{N}(\bar{y}_m | \mathbf{0}, \Sigma_k + \sigma^2 \mathbf{I}) - \ln C \quad (2)$$

Where C is the denominator in Eq. (2) and it is the same for all components. Finally, the component with the highest probability $\ln P(k|\bar{Y})$ is selected to process \bar{Y} .

PROPOSED METHODOLOGY

1. Initialization of a structure parameter and inputting of some parameters in it such as
 - Patch size
 - Number of non-local patches
 - Step of two neighbor patches
 - Number of iteration
 - Size of window around the patch
 - The variance of Gaussian white noise (sigma).
2. Loading of Gaussian Mixture Model.
3. Initialization of Gaussian dictionary and regularization parameter.
 - Gaussian dictionary i.e. Ortho-normal matrix composed by the eigenvectors.
 - Regularization parameter i.e. Diagonal matrix of Eigenvalues.
4. Reading and inputting of clean image.
5. Generation of a noisy image.
6. Display of noisy image and its PSNR normalized correlation coefficient and mean square error.
7. Calculation of size of the noisy image.

8. Computation of maximum rows by subtraction of patch size from row size of the noisy image.
9. Computation of maximum columns by subtraction of patch size from column size of the noisy image.
10. Computation of a maximum number of elements.
11. Computation of rows of the noisy image.
12. Computation of columns of the noisy image.
13. Computation of total steps in rows using the step of two neighbor patches.
14. Update of total steps by the addition of two more steps to it.
15. Computation of total steps in columns using the step of two neighbor patches.
16. Update of total steps by the addition of two more steps to it.
17. Counting of total updated row steps.
18. Counting of total updated column steps.
19. Computation of total rows and columns steps.
20. Iterative regularization
 - Declaration of a loop according to a number of iteration.
 - Application of denoising procedures for fixed iterations for better denoising outputs using iterative regularization strategy.
 - Update of the variance of noise (sigma) at each iteration.
 - Search non-local patch groups.
 - A. Record the non-local patch set and the index of each patch in seed patches in the image.
 - B. Conversion of updated noisy image into patches according to patch size.
 - C. Finding of the index of each patch in updated noisy image.
 - D. Record the indexes of patches similar to the seed patch.
 - E. Calculation of patch group means.
 - F. Declaration of the range indexes of the window for searching the similar patches.
 - G. Finding the patches around the seed (neighbor patches) in updated noisy image.
 - H. Conversion of patch group in patch vector.
 - I. Calculation of mean value of patch vector.
 - J. Subtraction of group means from patch vector.
 - Selection of the most suitable Gaussian component for each non-local patch groups.
 - Calculation of posterior probability that current non-local patch group belongs to the current Gaussian component.
 - Finding of the most likely component for each patch group.
 - Weighted Sparse Coding
 - A. Calculation of weighting vector to weight the coding vector (alpha).
 - B. Determination of non-local patch group
 - C. Calculation of coding vector.
 - Recovery of each patch in patch group.
 - Computation of weight matrix.
 - Reconstruction of cleaned image.
 - Construction of dummy matrix according to the size of original image.
 - Insertion of each patch group in image accordingly.
 - Calculation of output parameters i.e. PSNR and normalized correlation coefficient and mean square error at each iteration.
21. Calculation the PSNR, normalized correlation coefficient and mean square error for final cleaned image.

EXPERIMENTAL RESULTS

A modified method based on patch-based image modeling is proposed in this research work. The main part of proposed method is the use of image nonlocal self-similarity (NSS) prior. NSS prior refers to the fact that a local patch often has many nonlocal similar patches to it across the image. This fact significantly enhances the denoising performance. Patch Groups are extracted from training images by putting nonlocal similar patches into groups. According to these Patch Groups, Gaussian Mixture Model learning algorithm is developed to learn the NSS prior. The whole process is repeated 4 times to make the system learn more and more. The iteration process regulates and optimized some of the variables. These variables significantly affect the denoising performance. We have taken 3 images in this work for the testing purpose.

1. Japan.bmp
2. Parot.png
3. Cameraman.png

All 3 images have been inserted and tested one by one. Also, some input parameters are also have been taken which are such as:

- Patch size = 8
- Number of non-local patches = 10
- Step of two neighbor patches = 3
- Number of iteration = 4
- Size of window around the patch = 31
- Variance of Gaussian white noise (sigma) = 0.0875

The performance of proposed method has been given below in the form of snapshots. Figure 1 is the snapshot of original input image “japan.png”. Figure 2 is the snapshot of a noisy image. Figure 3 is the snapshot of the denoised image. Figure 4 is the snapshot of MATLAB command window having all the values of output parameters i.e. PSNR, Cross- Correlation and Mean square error. Similar snapshots are there from figure 5 to 12 for image “parot.bmp” and “cameraman.png”.

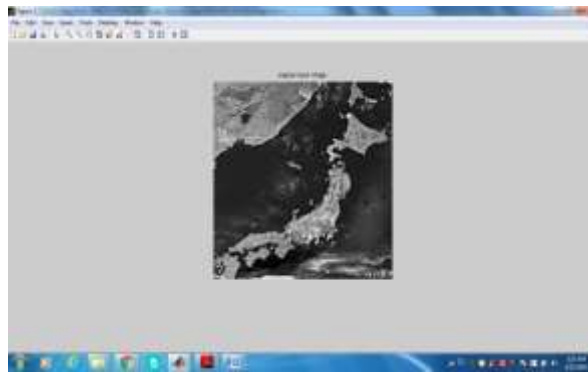


Figure 1 snapshot of original input image “japan.png”



Figure 2 snapshot of noisy image



Figure 3 snapshot of denoised image

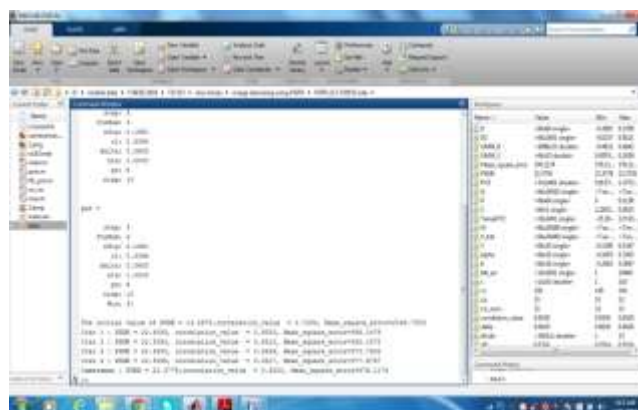


Figure 4 snapshot of MATLAB command window having all the Values of output parameters i.e. PSNR, Cross- Correlation and Mean square error

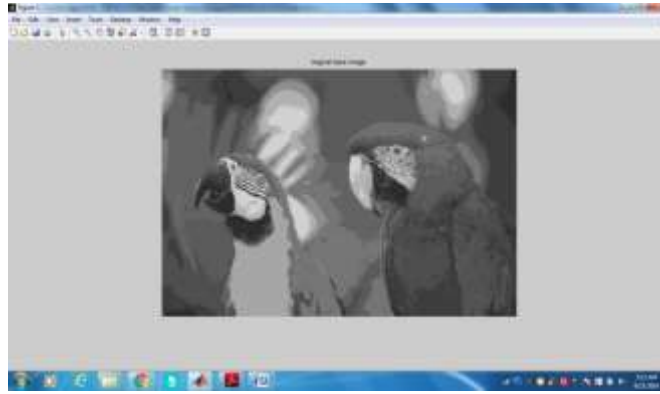


Figure 5 snapshot of original input image “parot.bmp”



Figure 6 snapshot of noisy image



Figure 7 snapshot of denoised image

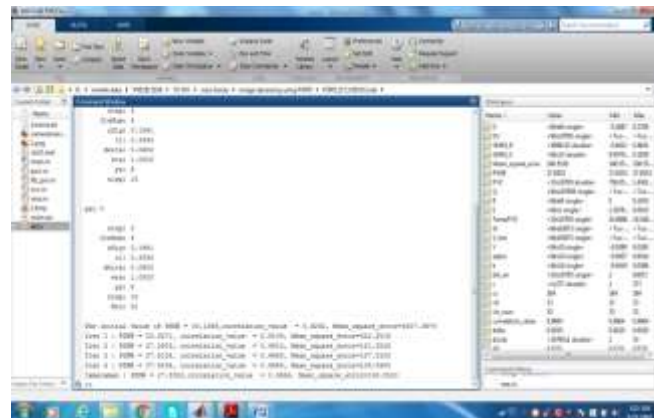


Figure 8 snapshot of MATLAB command window having all the Values of output parameters i.e. PSNR, Cross- Correlation and Mean square error



Figure 9 snapshot of original input image “cameraman.png”



Figure 10 snapshot of noisy image



Figure 11 snapshot of denoised image

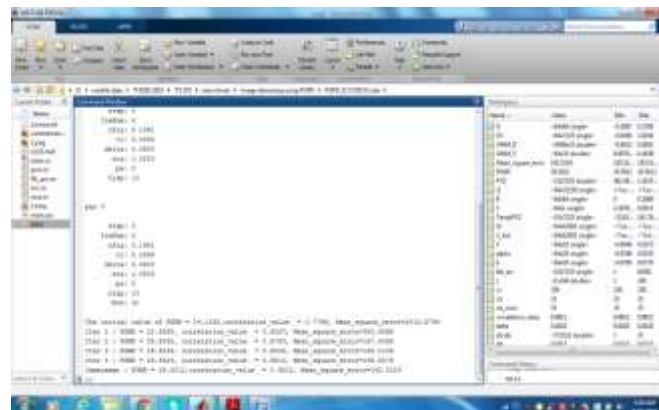


Figure 12 snapshot of MATLAB command window having all the values of output parameters i.e. PSNR, Cross- Correlation and Mean square error

CONCLUSION AND FUTURE SCOPE

It can be concluded that a modified method based on patch-based image modeling is proposed in this research work. Various state of the art method for the same challenge has been studied in this research work. Various applications now range from the casual documentation of events and visual communication to the more serious surveillance and medical fields. This has led to a rising demand for accurate and visually pleasing images. However, images captured by modern cameras are invariably corrupted by noise. Nowadays the concept of denoising is not restricted to the field of photography or publication where the image needs to be improved for printing purpose. It is a tool in a number of digital image processing application such as space exploration where noise can be introduced due to artifacts generated by the mechanical or optical system of a telescope. Image denoising finds application in the field of medical science where high-quality images are required in the form of x-ray images, ultrasound, and city scan images. A good quality medical image can be useful to diagnose diseases. In the field of forensic science, where evidence sometimes is available in extremely bad quality, in such case, denoising tools are used to produce quality images. Moreover core digital image processing applications like text extraction from images, number plate detection, OCR etc. use denoising as a pre-processing tool. Removing noising from digital images is still a challenging task. There are various methods available in literature but not a single method is suitable for all type of image noises.

The proposed method is working efficiently and effectively for the given challenges. The proofs of the above statement are the snapshot of the last chapter. PSNR of the proposed method is slightly higher than that of the existing system. Also, the proposed system is highly efficient and preserves better the image edges and textures. In future, the proposed system can be extended further to other image processing tasks such as deblurring and super-resolution.

REFERENCES

- [1] Dr. Balkrishan, Harmandeep Singh and Gurjeet Kaur "A Review on Image Denoising Methods" International Journal of Advanced Engineering and Global Technology I Vol-03, Issue-11, December 2015. Pp. 1380-1384.
- [2] Chatterjee, Priyam, and Peyman Milanfar. "Patch-based near-optimal image denoising." Image Processing, IEEE Transactions on 21.4 (2012): 1635-1649.
- [3] Xu, Jun, et al. "Patch Group Based Nonlocal Self-Similarity Prior Learning for Image Denoising." Proceedings of the IEEE International Conference on Computer Vision. 2015.
- [4] Zhang, Li, et al. "Multiple view image denoising." Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on. IEEE, 2009.
- [5] Ram, Bheem Prasad, and Sachi Choudhary. "Survey Paper on Different Approaches for Noise Level Estimation and Denoising of an Image." International Journal of Science and Research (IJSR) Volume 3 Issue 4, April 2014. Pp. 618-622.
- [6] Dubey, Priyank, and Samidha D. Sharma. "A Survey Paper on Noise Estimation and Removal through Principal Component Analysis." International Journal of Emerging Technology and Advanced Engineering Volume 3, Issue 6, June 2013). Pp. 364-366.
- [7] Guo, Qiang, et al. "An efficient SVD-based method for image denoising." (2015).