

DWT based Novel Image Denoising by Exploring Internal and External Correlation

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ABSTRACT: Removing noise from the original image is still a challenging problem for researchers. In this paper, we build the internal and external data cubes to finding the similar patches from the noisy and web images respectively. We proposed two-stages using different filtering approaches for reducing noise. By combining the internal and external de-noising patches, we obtain a preliminary de-noising result. In the second stage, we propose reducing noise by filtering of external and internal cubes, respectively, on transform domain. In this stage, the preliminary de-noising result not only enhances the patch matching accuracy but also provides reliable estimates of filtering parameters. The final de-noising image is obtained by fusing the external and internal filtering results process. The proposed system shows the obsolete de-noising results with the accurate measurements, and its compared with existing BM3D result, Low-rank based result, EPLL^g result, EPLL^s.

KEYWORDS: Image de-noising, external correlations, internal correlations, Discrete wavelet transforms (DWT)

I. INTRODUCTION

Digital image plays an important role in our daily life and in the area of research and technology. When the digital image is transmitted from one place to another place, during the transmission noise is added into the image. Any form of signal processing having image as an input and output is called image processing. Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image [1-3]. There are two types of methods used for image processing namely, analogue and digital image processing. The purpose of image processing is divided

into 5 groups. They are Visualization, Image sharpening and restoration, Image retrieval, Measurement of pattern, Image Recognition.

Digital images are often degraded by noise in the acquisition and transmission phase. The goal of image de-noising is to recover the true original image from such a distorted noisy copy. The presence of noise not only produces undesirable visual quality but also lowers the visibility of low contrast objects. The image usually has noise which is not easily eliminated in image processing. According to actual image characteristic, noise statistical property and frequency spectrum distribution rule, people have developed many methods of eliminating noises, which approximately are divided into space and transformation fields. The space field is data operation carried on the original image, and processes the image grey value, like neighborhood average method, wiener filter, center value filter and so on. Various types of noise present in image are Gaussian noise, Salt & Pepper noise and Speckle noise [1]. Image de-noising techniques are used to prevent these types of noises while retaining the important signal features [1]. Poor image sensors, imperfect instruments, problems with data acquisition process, transmission errors and interfering natural phenomena are its main sources [4-5]. Therefore, it is necessary to detect and remove noises present in the images. Reserving the details of an image and removing the random noise as far as possible is the goal of image de-noising approaches.

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In this paper Section II describes the related work. Section III illustrate the results and discussions. Section IV concludes the paper.

II. RELATED WORK

De-An Huanget *al* [6], have proposed novel self-learning based image decomposition framework. Based on the recent success of sparse representation, the proposed framework first learns an over-complete dictionary from the high spatial frequency parts of the input image for reconstruction purposes.

Madison Gray McGaffin *et al* [7] have proposed image de-noising algorithms for edge preserving regularization that play to the strengths of GPUs, the exemplar of this parallelism trend. By avoiding operations like inner products or complex preconditioners and minimizing memory usage, the proposed GCD algorithms provide impressive convergence rates. The additional increase in performance provided by Nesterov’s first-order acceleration is exciting.

Xianhua Zeng *et al* [10], have proposed a two-dimensional image de-noising model, namely, the Dictionary Pair Learning (DPL) model, and we design a corresponding algorithm called the Dictionary Pair Learning on the Grassmann-manifold (DPLG) algorithm.

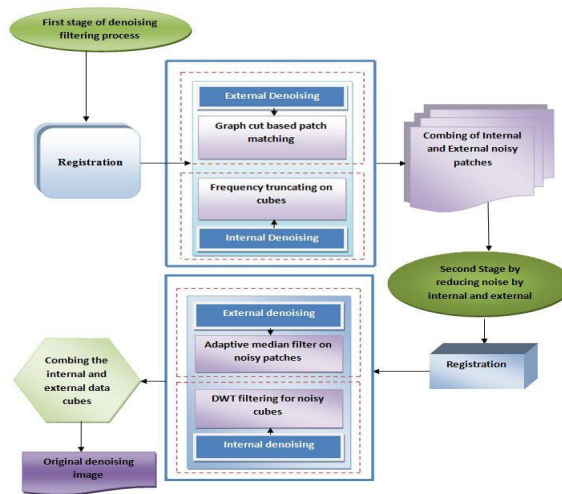


Fig. 1. Proposed Method

Given a noise free image P^0 (the superscript o denotes original), its noisy version P is produced as

$$P = P^0 + N \quad (1)$$

Where N is the additive zero-mean independent identically distributed (i.e.) Gaussian noise with variance σ^2 . We aim to recover, the estimated noise free version of P , with the help of web images.

For one noisy input P , we retrieve its correlated images $\{P_1^r, P_2^r, \dots, P_k^r\}$ (the superscript r denotes reference images) from web images using content based image retrieval technology. Given I and $\{P_1^r, P_2^r, \dots, P_k^r\}$, we propose a two-stage based de-noising scheme, which is illustrated in Fig. 1.

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A. Correlated Image Retrieval and Registration

The local features such as SIFT are usually of different scales and overlapped with each other. We believe the inclusion relationship among local features provides a natural way to construct visual phrases for geometric verification. Previous learning based de-noising methods ignore content priors in a noisy image, which limits improvement in de-noising performance. Therefore, we adopt content-based image retrieval technology, specifically the scale invariant feature transform (SIFT) based method proposed in [26] to retrieve correlated images from a large-scale database, as our external dataset. Since a large scale SIFT feature may cover multiple small scale SIFT features. After matching all the visual groups extracted from the noisy image with those extracted from candidate images, we obtain a set of correlated images $\{P_1^r, P_2^r, \dots, P_k^r\}$. For more details; please refer to [26]. Note that, to reduce the impact of noise in feature extraction, we discard some key-points with low contrast.

B. Graph Based Optimization Method-External De-Noising using Baseline Method:

An intuitive method is to use ℓ_2 distances as the matching criterion. Let $t_i = \{\Delta x_i, \Delta y_i, \Delta z_i\}$ be the translation vector (in col, row, and image number directions) of the t_i patch from the noisy image to the reference images. We want to find the optimal translation for each patch by minimizing the following function:

$$E(t) = \sum_i D(X_i, Y(t_i)), \quad (2)$$

Where $D(X_i, Y(t_i))$ is ℓ_2 distance of patch P_i and the candidate patch Q with translation t_i . Note that the mean values of all the candidate patches and the noisy query have been removed to reduce illumination effect.

The translation vectors are obtained by minimizing the following energy function:

$$E(t) = \sum_i D(X_i, Y(t_i)) + \beta \sum_{(i,j) \in N} S(t_i, t_j) \quad (3)$$

Where $D(X_i, Y(t_i))$ is the same as that defined in Eq. 3 $S(t_i, t_j)$ is the smoothness term, β is a weighting parameter to adjust the effect of the smooth constrain and $(i, j) \in N$ denotes that the i^{th} and j^{th} patch are neighboring patches. In this paper, N is a four connected grid. The smooth term S penalizes the differences of neighboring translation vectors,

defined as

$$S(t_i, t_j) = \begin{cases} \min(\|t_i - t_j\|_1, \xi_1), & \text{if } \Delta z_i - \Delta z_j = 0 \\ \xi_2, & \text{otherwise} \end{cases} \quad (4)$$

C. Second Stage Reducing Noise by Filtering Process

The first stage de-noising result I^{1st} has greatly reduced the noise. Therefore it could help to improve the de-noising performance in the second stage. A similar strategy is proposed in BM3D [2] and have achieved significant gain compared with the first stage de-noising result. In this section, we will first introduce Wiener filtering in image de-noising, and then apply it to our internal and external de-noising scheme.

D. De-Noising by Dwt Process

The wavelet transform is a type of signal transform that is commonly used in compression or for decomposition of the error signal. A newer alternative to wavelet transform is the discrete wavelet transforms. Multi wavelets are very similar to wavelets but have some important differences. In particular, Multi wavelets have two or more scaling and

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 6, June 2016

wavelet functions whereas wavelets have an associated scaling function $\phi(t)$ and wavelet function $\psi(t)$. The set of scaling functions can be written as $\phi(t) = [\phi^1(t), \phi^2(t), \dots, \phi^r(t)]^T$, where $\phi(t)$ is called the multi scaling function. Likewise, the Multi wavelet function is defined from the set of wavelet functions as $\psi(t) = [\psi_1(t), \psi_2(t), \dots, \psi_r(t)]^T$.

Where, T is denoted as the vector response and r can be arbitrarily large (where $r=2$) [31]. The multi wavelet relation of low pass filter and high pass filter is as follows.

$$\phi(t) = \sqrt{2} \sum_{k=0}^{n-1} R_k \phi(2t - k) \quad (5)$$

$$\psi(t) = \sqrt{2} \sum_{k=0}^{n-1} L_k \psi(2t - k) \quad (6)$$

Where, H_k is the low pass filter coefficient and G_k is the high pass filter coefficient. The speed error of the IPMSM drive system is applied as an input to the multi wavelet network, so that the error gets decomposed. In multi wavelet transform, the decomposition produces --two low-pass sub-bands, two high-pass sub-bands and two sets of wavelet coefficients for the each level of decomposition. This transformation detects and extracts disturbance features in the form of low and high frequency information. Multi scaling functions and Multi wavelet functions available in multi wavelets led to better decomposition of error in each level of decomposition.

E. De-Noising by Exploring External Correlations

The noise in \tilde{I}^{1st} is assumed to be greatly attenuated. Therefore, for each patch \tilde{P}^{1st} in \tilde{I}^{1st} , we can directly retrieve its k_2 -NN patches $\{Q_1, Q_2, \dots, Q_k\}$ from the external image set $\{P_1^r, P_2^r, \dots, P_k^r\}$ using the baseline method described in Sec. V-A. These patches $\{q_1^r, q_2^r, \dots, q_k^r\}$ (in vector format) can be regarded as sample realizations of P^0 . Note that DC components of $\{q_1, q_2, \dots, q_k\}$ and p are removed before patch matching to reduce illumination effects. Therefore, the matrix R is estimated as:

$$R = \frac{1}{k_2} \sum_{i=1}^{k_2} Y_i Y_i^T$$

$$R = \frac{1}{k_2} Y_{2D} Y_{2D}^T$$

III. RESULT AND DISCUSSION

Our proposed DWT method performance is analyzed by comparing the existing technique such as BM3D, LOW RANK, EPLLg and EPLLs with our proposed technique. The sample image which is utilized in the image de-noising is given below in figure 2 to figure 5. the PSNR value of the proposed DWT based de-noising technique is compared with the existing BM3D, Low-rank, EPLLg, EPLLs.

International Journal of Innovative Research in Science, Engineering and Technology

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Vol. 5, Issue 6, June 2016



Fig. 2. Shows the sample images taken from the database



Fig. 3. Shows the grey scale images



Fig.4. Shows the noise images



Fig. 5. Shows the de-noised image.

TABLE I

PSNR & SSIM COMPARISON

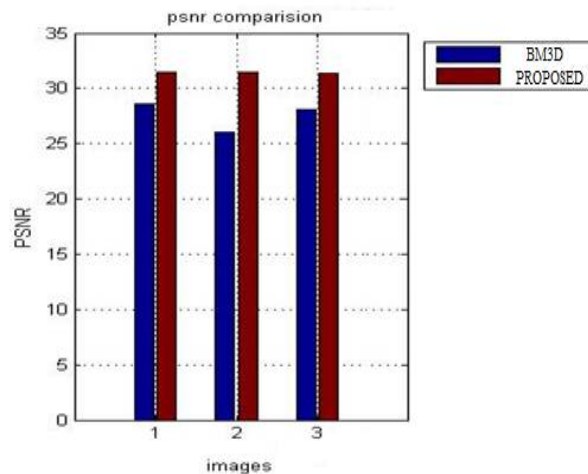
Image	BM3D	BM3D	Proposed	Proposed
	PSNR	SSIM	PSNR	SSIM
a	28.56	0.819	31.5093	0.8644
b	26.05	0.748	31.5096	0.85258
c	28.08	0.802	31.3684	0.81036

From the table it has been shown that the PSNR value of the proposed technique is higher than the existing techniques.

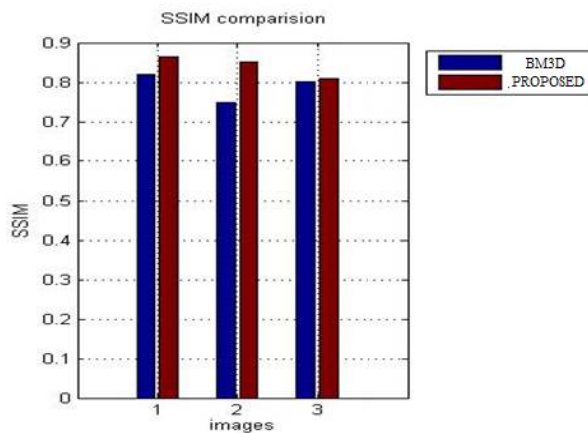
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(An ISO 3297: 2007 Certified Organization)

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Similarly the SSIM values of the proposed dwt and existing BM3D method was compared.



The SSIM value of the proposed techniques gives higher performance ratio than the existing technique

IV. CONCLUSION

We have proposed two stages of different filtering approaches. In the first stage external de-noising part, a graph-cut based patch matching accuracy. The internal de-noising part is performed on similar noisy patches by filtering in the transform domain. In the second stage reducing noise by filtering process. Then, to improve the second stage de-noising result; we have proposed DWT for filtering on noisy cubes in internal de-noising. By combining the internal and external de-noising patches, we obtain the final de-noising result. The experimental results demonstrate that our proposed de-noising method achieve competitive performance than other existing methods.

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Vol. 5, Issue 6, June 2016

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