International Journal of Engineering Research and General Science Volume 3, Issue 3, May-June, 2015
ISSN 2091-2730

An Improved Approach For Mixed Noise Removal In Color Images

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Abstract— Denoising is a fundamental problem in image processing. Mixed noise removal from natural images is a challenging task since the noise distribution usually does not have a parametric model and has a heavy tail. Two types of commonly encountered noise are additive white Gaussian noise (AWGN) and impulse noise (IN). Many of the existing mixed noise removal methods are detection based methods. They first detect the locations of IN pixels and then remove the mixed noise. However, they tend to introduce artifacts. In this paper, we propose a simple method using weighted encoding coupled with alpha-trimmed mean filter to remove the mixed noise distribution effectively. The performance of our approach is experimentally verified on a variety of images and noise levels. The results presented here demonstrate that our proposed method is exceeding the current state of the art methods, both visually and quantitatively.

Keywords— Alpha-trimmed mean, adaptive, fuzzy filter, mixed noise removal, nonlocal, sparse representation, PCA dictionary, weighted encoding.

1 INTRODUCTION

Digital images maybe contaminated either during either the image acquisition or image transmission. Our aim is to estimate the original image from its corresponding noise-corrupted image while preserving as much as possible the image edges and textures. The additive white Gaussian noise(AWGN) is often introduced due to thermal motion of electrons in camera sensors and circuits. Impulse noise(IN) is often introduced by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or bit errors in transmission [1].Two types of widely encountered IN are salt-and pepper impulse noise (SPIN) and random-valued impulse noise(RVIN).

A variety of mixed-noise removals have been proposed in the past years. Nonlinear filters such as median filters [3] have been dominantly used to remove IN. However, one shortcoming of median filters is that the image local structures can be destroyed, making the denoised images look unnatural. The weighted median filter, the center-weighted median filter and the multistate median filter[12] do not distinguish whether the current pixel is a noise pixel or not, and they tend to over-smooth the fine scale image details. Traditional linear filtering methods such as Gaussian filtering can smooth AWGN efficiently but they will over-smooth the image edges at the same time. To solve this problem, nonlinear filtering methods have been developed. The well-known bilateral filter (BF) [4] is good at edge preservation. It estimates each pixel as the weighted average of the neighboring pixels but the weights are determined by both the intensity similarity and spatial similarity.

The mixture of IN and AWGN, however, makes the denoising problem much more difficult because of the very different properties of the two types of noises. The median-based signal-dependent rank ordered mean (SDROM) filter [5] can be used for IN removal as well as mixed noise removal. However, when applied to image with mixed noise, it often produces visually unpleasant artifacts. Liu et al. [6] proposed a weighted dictionary learning model for mixed noise removal. This method integrates sparse coding and dictionary learning, image reconstruction, noise clustering and parameters estimation into a four-step framework, and each step solves a minimization problem.

Many existing mixed noise removal methods are detection based methods and they involve two sequential steps, i.e., first detect the IN pixels and then remove the noise. Such a two-phase strategy will become less effective when the AWGN or IN is strong. In this paper, we propose a simple yet effective encoding based method for mixed noise removal, weighted encoding with sparse nonlocal regularization(WESNR) along with alpha-trimmed mean filter. There is no explicit impulse pixel detection in WESNR[1], and an alpha-trimmed mean filter[2] is used to remove the SPIN initially. Each noise-corrupted patch is encoded over a pre-learned dictionary to remove the IN and AWGN simultaneously. The mixed noise is suppressed by weighting the encoding residual so that the final encoding residual will tend to follow Gaussian distribution. Extensive experiments are conducted to validate the proposed method in comparison with state-of-the-art mixed noise removal methods. Also, this method has been experimented on both grayscale and color images.

2 PROPOSED METHOD

2.1 Alpha-Trimmed Mean Filter

We propose a two-stage iterative, adaptive, fuzzy filter for removing the SPIN in the image. The α-trimmed mean computes the mean of a set of elements after trimming the top and bottom α/2 elements of the set. The α-trimmed mean of a set A = {a1, a2, ..., an} of n elements is thus given by

$$\mu_\alpha = \frac{1}{n-\alpha} \sum_{i=(\alpha/2)+1}^{n-(\alpha/2)-1} a_i \qquad (1)$$

where a_i is the i-th order statistic of the elements of A.

The *mean of* k-*middle*, is denoted by $M_k(A)$:

$$\mathcal{M}_k(A) = \begin{cases} \frac{1}{2k-1} \sum_{i=h-k+1}^{h+k-1} a_i & \text{if } n \text{ is odd } (n = 2h-1), \\ \frac{1}{2k} \sum_{i=h-k+1}^{h+k} a_i & \text{if } n \text{ is even } (n = 2h), \end{cases} \qquad (2)$$

The detection and denoising of SPIN pixels is done as in [2].

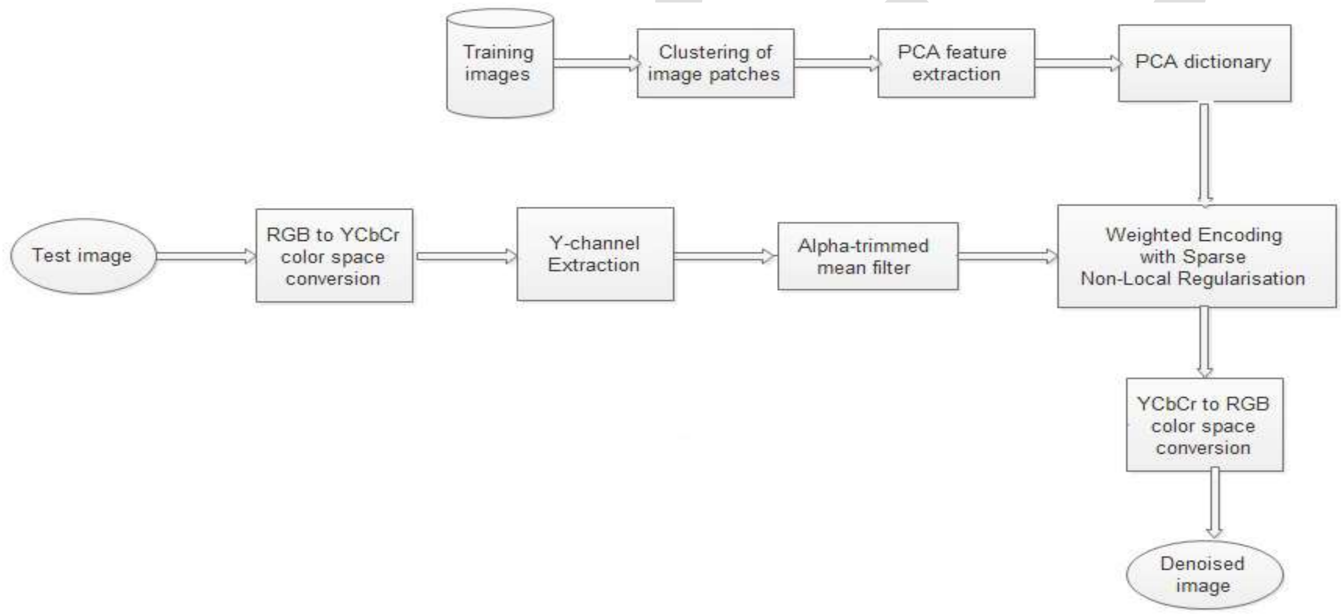


Fig. 1 The block diagram of the proposed method

2.2 Mixed Noise Removal Model

A novel weighted encoding model is proposed to remove mixed noise, which does not have an explicit impulse pixel detection step and can process AWGN and IN simultaneously. We denote an image as $\boldsymbol{p} \in \boldsymbol{R}^N$. The stretched vector of an image patch of size $\sqrt{n}\times\sqrt{n}$, can be represented by $\boldsymbol{p}_i = \boldsymbol{R}_i\boldsymbol{p} \in \boldsymbol{R}^n$, where $\boldsymbol{R}_i$ is the matrix operator extracting patch p_i from p at location $\boldsymbol{i}$ as in [1]. Based on the sparse representation theory [7], we can find an over-complete dictionary $\boldsymbol{\Phi} = [\boldsymbol{\Phi}_1; \boldsymbol{\Phi}_2; \ldots; \boldsymbol{\Phi}_n] \in \boldsymbol{R}^{n\times m}$ to sparsely code $\boldsymbol{p}_i$, where $\boldsymbol{\Phi}_j \in \boldsymbol{R}^n$ is the j^{th} atom of $\boldsymbol{\Phi}$. The representation of $\mathbf{p}_i$ over dictionary $\boldsymbol{\Phi}$ can be written as $p_i = \boldsymbol{\Phi}\boldsymbol{\alpha}_i$, where $\boldsymbol{\alpha}_i$ is a sparse coding vector with only a few non-zero entries.

The above equation can be re-written as

$$\boldsymbol{p} = \boldsymbol{\Phi}\boldsymbol{\alpha} \qquad (3)$$

The observation of $\boldsymbol{p}$ that we have is noise-corrupted, and we can only encode the noisy observation $\boldsymbol{y}$ over the dictionary $\boldsymbol{\Phi}$ to obtain the desired $\boldsymbol{\alpha}$. In the case of AWGN, the encoding model can be generally written as

$$\hat{\alpha} = \arg\min_{\alpha} \|\boldsymbol{y} - \boldsymbol{\Phi}\boldsymbol{\alpha}\|_2^2 + \lambda R(\boldsymbol{\alpha}), \qquad (4)$$

where $R(\boldsymbol{\alpha})$ is some regularization term imposed on $\boldsymbol{\alpha}$ and λ is the regularization parameter. In the case of mixed noise, however, the distribution of noise is generally far from Gaussian and thus the l_2-norm data fidelity term in Eq. (4) $\|\boldsymbol{y} - \boldsymbol{\Phi}\boldsymbol{\alpha}\|_2^2$ will not lead to a MAP solution for noise removal.

From Fig. 2(a), we can see that the distribution of data fitting residual is much more irregular than Gaussian, and it has a heavy tail.

Naturally, if the datafidelity term can be modified so that the residual can be more Gaussian-like, then the l_2-norm can still be used to characterize the coding residual. This motivates us to use the robust estimation technique [8], [9] to weight the data fitting residual so that its distribution can be more regular.

Let $\boldsymbol{e} = [e_1; e_2; \ldots ; e_N] = \boldsymbol{y} - \boldsymbol{\Phi\alpha}$, (5)

where $e_i = (\boldsymbol{y} - \boldsymbol{\Phi\alpha})(i)$. Assume that $e_1, e_2, \ldots, e_N$ are i.i.d. samples. We need to minimize the following loss:

$\min \sum_{i=1}^{N} f(e_i)$ (6)

when $f(e_j) = e_j^2$, the model in Eq. (6) reduces to Eq. (5). In order to weaken the effect of the heavy tail in mixed noise distribution, we can assign each residual a proper weight, resulting in a weighted residual:

$$e_i^w = w_i^{1/2} e_i \quad (7)$$

From Fig. 2(b), we can see that the distribution of weighted residuals is much closer to Gaussian distribution, implying that l_2-norm can be used to model the weighted residuals for a MAP-like solution of coding vector $\boldsymbol{\alpha}$. Now, we have a new model for mixed noise removal using Eq. (7):

$$\hat{\alpha} = \arg\min_{\alpha} \|W^{1/2}(y - \Phi\alpha)\|_2^2 + \lambda R(\alpha), \quad (8)$$

where $\boldsymbol{W}$ is a diagonal weight matrix with diagonal element $\boldsymbol{W}_{ii} = \boldsymbol{w}_i$. To make our method more effective for mixed noise removal, some regularization terms $R(\boldsymbol{\alpha})$ can be used based on the priors of natural images. Two priors are widely used in image denoising: local sparsity and nonlocal self-similarity (NSS) [10]. The local sparsity of encoding coefficients $\boldsymbol{\alpha}$ can be characterized by the l_1-norm of $\boldsymbol{\alpha}$, while the NSS can be characterized by the prediction error of a patch by its similar patches.

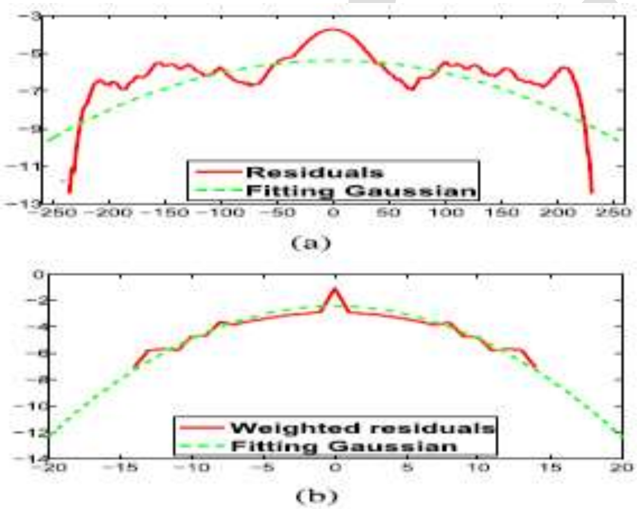


Fig. 2. (a) The distribution of residuals e_i and the fitting Gaussian in log domain. (b) The distribution of weighted residuals $w_i^{1/2} e_i$ and the fitting Gaussian in log domain.

Finally, the proposed model becomes:

$$\hat{\alpha} = \arg\min_{\alpha} \{\|W^{1/2}(y - \Phi\alpha)\|_2^2 + \lambda\|\alpha - \mu\|_1\} \quad (9)$$

where α_i and μ_i are the coding coefficients of a patch p_i and its non-local prediction; l_1-norm, since α_i-μ_i follows the Laplacian distribution.

Algorithm 1: Mixed Noise Removal

Input: Dictionary $\boldsymbol{\Phi}$, noisy image $\boldsymbol{y}$;

Initialize $\boldsymbol{e}$ by Eq. (13) and then
initialize $\boldsymbol{W}$ by Eq (10);
Initialize $\boldsymbol{\mu}$ to 0.

Output: Denoised image $\boldsymbol{p}$.

Loop: iterate on k=1,2,..,K;

1. Compute $\boldsymbol{\alpha}^k$ by Eq.(12);
2. Compute $\boldsymbol{p}^k = \boldsymbol{\Phi\alpha}^k$ and update the nonlocal coding vector $\boldsymbol{\mu}$;
3. Compute the residual $\boldsymbol{e}^k = \boldsymbol{y} - \boldsymbol{p}^k$
4. Calculate the weights $\boldsymbol{W}$ by $\boldsymbol{e}^k$ using Eq.(10);

End

Output the denoised image $\boldsymbol{p} = \boldsymbol{\Phi\alpha}^k$

The $\boldsymbol{W}$ in Eq (9) ensures that the pixels corrupted by IN will have small weights to reduce their effect on the encoding of $\boldsymbol{y}$ over $\boldsymbol{\Phi}$, while the weights assigned to uncorrupted pixels should be close to 1.Therefore, the coding residual $\boldsymbol{e}_i$ can be used to guide the setting of weight $\boldsymbol{W}_{ii}$, and $\boldsymbol{W}_{ii}$ should be inversely proportional to the strength of $\boldsymbol{e}_i$. In order to make the weighted encoding stable and easy to control, we set $W_{ii} \in [0,1]$. One simple and appropriate choice of W_{ii} is

$$W_{ii} = \exp(-a e_i^2), \qquad (10)$$

where a is a positive constant to control the decreasing rate of $\boldsymbol{W}_{ii}$ w.r.t. $\boldsymbol{e}_i$. the pixels corrupted by IN will be adaptively assigned with lower weights to reduce their impact in the process of encoding. The method follows iteratively reweighted scheme for its simplicity. Let $\boldsymbol{V}$ be a diagonal matrix. We first initialize it as an identity matrix, and then in the $(k+1)^{th}$ iteration, each element of $\boldsymbol{V}$ is updated as

$$V_{ii}^{(k+1)} = \lambda/((\alpha_i^{(k)} - \mu_i)^2 + \varepsilon^2)^{1/2}, \qquad (11)$$

where ϵ is a scalar and $\alpha^{(k)}i$ is the i^{th} element of coding vector $\boldsymbol{\alpha}$ in the k^{th} iteration. Then we update $\boldsymbol{\alpha}$ as

$$\hat{\alpha}^{(k+1)} = (\Phi^T W \Phi + V^{(k+1)})^{-1}(\Phi^T W y - \Phi^T W \Phi \mu) + \mu \qquad (12)$$

The desired $\boldsymbol{\alpha}$ can be obtained by iteratively updating $\boldsymbol{V}$ and $\boldsymbol{\alpha}$.

2.3 The Dictionary

We use the same 5 high-quality images (which are independent of the test images used in this paper) as in [11] to train the PCA dictionaries. A number of 876,359 patches (size: 7×7) are extracted from the five images and they are clustered into 200 clusters by using the K-means clustering algorithm. For each cluster, a compact local PCA dictionary is learned. Meanwhile, the centroid of each cluster is calculated. For a given image patch, the Euclidian distance between it and the centroid of each cluster is computed, and the PCA dictionary associated with its closest cluster is chosen to encode the given patch.

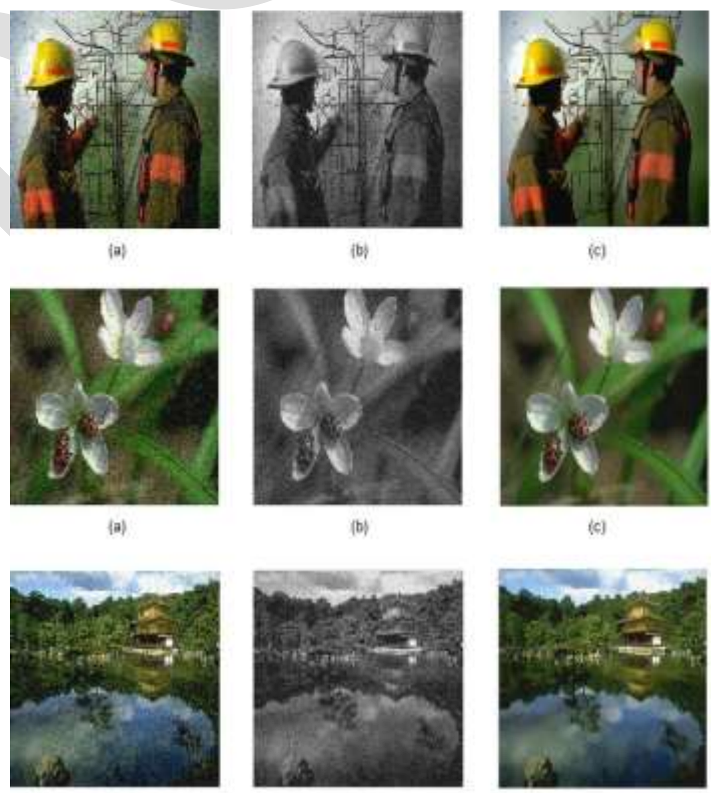
2.4 Algorithm of WESNR

Once the dictionary $\boldsymbol{\Phi}$ is adaptively determined for a given patch, the proposed WESNR model can be solved by iteratively updating $\boldsymbol{W}$ and $\boldsymbol{\alpha}$. The updating of $\boldsymbol{W}$ depends on the coding residual $\boldsymbol{e}$. We use alpha-trimmed mean filter [2] to $\boldsymbol{y}$ to obtain an initialized image $\boldsymbol{p}^{(0)}$,and then initialize e as:

$$\boldsymbol{e}^{(0)} = \boldsymbol{y} - \boldsymbol{p}^{(0)}, \qquad (13)$$

(a) (b) (c)

Fig. 3. Gray-scale images (a) Input image. (b) Noise added image. (c) Denoised image



(a) (b) (c)

Fig. 4. Color images (a) Noisy RGB image. (b) Noisy YCbCr image. (c) Denoised RGB image

Currently, this project is employed in gray scale images. As a next step, this method is applied to the problem of denoising color images. It is seen that frequencies at which the human eye perceives each of the red, green, and blue (RGB) colors have considerable overlap. Consequently, many color denoising methods take into account such dependencies, either implicitly or explicitly.

An important approach to treating such correlated color information is through color-space conversion where the information between color spaces can be largely decorrelated. Here, the RGB color-space is converted into the YCbCr color-space; and the Y-channnel is extracted which contains the luminance channel, to which the human visual system is more sensitive. The denoising is performed on the Y-channel and then combined back which is then converted back from YCbCr color-space to RGB color- space.

3 RESULTS AND PERFORMANCE ANALYSIS

A set of 5 high-quality images are used to train the PCA dictionaries. Note that the images used for training the dictionary will not affect the denoising of test images. Some examples of denoising gray-scale and color images are shown in Fig. 3 and Fig. 4.

The experiments have been conducted on various images using adaptive median filter and alpha-trimmed mean filter. A comparison of various methods has been shown in the table below:-

TABLE 1

PSNR (DB) RESULTS OF MIXED NOISE REMOVAL(AWGN+RVIN+SPIN)

Image	Noise level	TF	ROR-NLM	BM3D	WESNR	Proposed method
Lena	σ=5,s=0.5	17.71	24.93	26.57	31.80	35.75
	σ=10,s=0.4	22.51	27.87	26.88	30.34	34.64
	σ=15,s=0.3	25.05	27.01	26.32	28.47	33.30
Boat	σ=5,s=0.5	16.15	22.79	23.60	28.23	30.69
	σ=10,s=0.4	20.39	25.37	23.84	27.32	30.12
	σ=15,s=0.3	22.57	25.14	23.48	26.13	29.62
Couple	σ=5,s=0.5	16.05	22.74	23.49	28.18	30.59
	σ=10,s=0.4	20.31	25.36	23.74	27.21	30.52
	σ=15,s=0.3	22.54	25.06	23.34	26.05	29.25
Fingerprint	σ=5,s=0.5	13.40	21.00	19.73	26.45	28.79
	σ=10,s=0.4	16.49	23.64	19.94	25.16	28.97
	σ=15,s=0.3	18.41	22.73	19.44	23.50	27.82
Man	σ=5,s=0.5	17.02	24.02	24.99	29.10	30.74
	σ=10,s=0.4	21.44	26.47	25.25	28.13	30.67
	σ=15,s=0.3	23.75	25.91	24.81	26.80	29.43

A performance comparison of the proposed method has been shown in the graph below:-

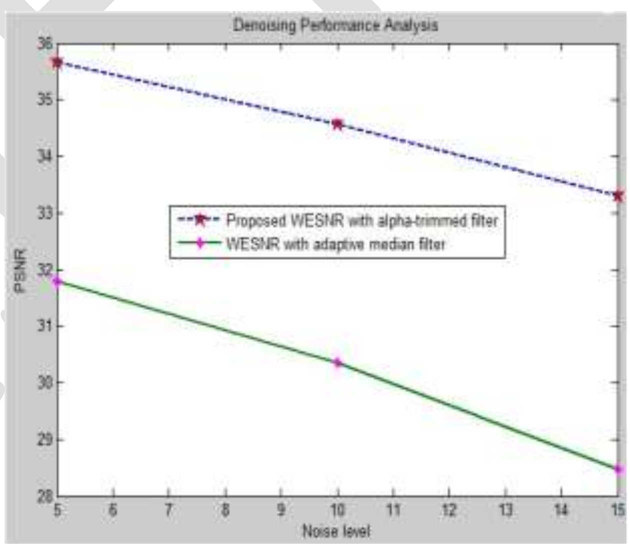


Fig. 5. Performance Analysis Graph

4 CONCLUSION

A novel model for mixed noise removal is presented in this paper. The distribution of mixed noise, e.g., additive white Gaussian noise mixed with impulse noise, is much more irregular than Gaussian noise alone, and often has a heavy tail. First, an alpha-trimmed mean filter is applied to the image to remove the SPIN effectively. To remove the remaining mixed noise, the weighted encoding technique is adopted to remove Gaussian noise and impulse noise jointly. The image patches are encoded over a set of PCA dictionaries learned online, and weighted the coding residuals to suppress the heavy tail of the distribution. Meanwhile, image sparsity prior and nonlocal self-similarity prior were integrated into a single nonlocal sparse regularization term to enhance the stability of weighted encoding.

The method has been tested on grayscale and color images. The results clearly demonstrated that the proposed method outperforms much other state-of-the-art mixed noise removal methods.

REFERENCES:

[1] Jielin Jiang, Lei Zhang, and Jian Yang, "Mixed Noise Removal by Weighted Encoding With Sparse Nonlocal Regularization", *IEEE Transactions On Image Processing*, Vol. 23, No. 6, June 2014

[2] Faruk Ahmed and Swagatam Das, "Removal of High Density Salt-and-Pepper Noise in Images with an Iterative Adaptive Fuzzy Filter using alpha-trimmed Mean", *IEEE Transactions On Fuzzy Systems*, Vol. 22, No. 10, Oct 2013

[3] I. Pitas and A. N. Venetsanopoulos, "Nonlinear Digital Filters: Principles and Applications". Norwell, MA, USA: Kluwer, 1990

[4] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in Proc. IEEE 6th Int. Conf. Comput. Vis., Jan. 1998, pp. 839-846.

[5] E. Abreu, M. Lightstone, S. K. Mitra, and K. Arakawa, “A new efficient approach for the removal of impulse noise from highly corrupted images,” *IEEE Trans. Image Process.*, vol. 5, no. 6, pp. 1012–1025, Jun. 1996.

[6] J. Liu, X.-C. Tai, H. Huang, and Z. Huan, “A weighted dictionary learning models for denoising images corrupted by mixed noise,” *IEEE Trans. Image Process.*, vol. 22, no. 3, pp. 1108–1120, Mar. 2013.

[7] M. Elad, M. A. T. Figueiredo, and Y. Ma, “On the role of sparse and redundant representations in image processing,” *Proc. IEEE*, vol. 98, no. 6, pp. 972–982, Jun. 2010.

[8] M. Yang, L. Zhang, J. Yang, and D. Zhang, “Regularized robust coding for face recognition,” *IEEE Trans. Image Process.*, vol. 22, no. 5, pp. 1753–1766, May 2013.

[9] P. J. Huber, *Robust Statistics*. New York, NY, USA: Wiley, 1981.

[10] W. Dong, L. Zhang, G. Shi, and X. Li, “Nonlocally centralized sparse representation for image restoration,” *IEEE Trans. Image Process.*, vol. 22, no. 4, pp. 1620–1630, Apr. 2013.

[11] W. Dong, L. Zhang, G. Shi, and X. Wu, “Image deblurring and super resolution by adaptive sparse domain selection and adaptive regularization,” *IEEE Trans. Image Process.*, vol. 20, no. 7, pp. 1838–1857, Jul. 2011.

[12] A. Nieminen, P. Heinonen, and Y. Neuvo, “A new class of detail preserving filters for image processing,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 9, no. 1, pp. 74–90, Jan. 1987