

Smooth region's mean deviation-based denoising method

S. Suhaila, R. Hazli, and T. Shimamura

Abstract—This paper presents a denoising method to preserve the image fine details and edges while effectively reducing the additive noise. The denoising method is performed in a two-phase process. The first process reduces noise in the corrupted image to a certain level by using a small filtering window to ensure that the image fine details and edges are still preserved. Then, further denoising is performed only in the smooth regions by using a bigger filtering window to remove the remaining noise more effectively. The use of two different filtering window sizes in the processes is important to achieve an optimum preservation of the image fine details and edges. The utilization of the mean deviation in the determination of the threshold value contributes to a more accurate division of smooth and nonsmooth regions. The performance of the proposed denoising method is investigated by the visual effects, method noise and objective image quality evaluation. Simulation results demonstrate that the proposed method is effective for preserving the image fine details and edges while eliminating the noise. This method provides high performance for all evaluation criteria in comparison to the conventional approaches.

Keywords—Fine details and edges preservation, Image denoising, Mean deviation, Smooth region.

I. INTRODUCTION

Developing a denoising method that is capable of suppressing additive noise totally from a noisy image without corrupting the image details, is still a challenging problem. The task is especially difficult in images that are rich in textures and edges. Until recent years, many related denoising methods with different approaches have been proposed [1]-[6], based on linear and nonlinear denoising methods.

Generally, linear filters [7][8] degrade the edges and produce blurrer image. However, if the image pixel intensities are nearly constant (without edges), and if the image is degraded by the additive white Gaussian noise (AWGN), the linear filters are the best in the sense of the least squares and the maximum of probability [9]. The Wiener filter is a well-known linear filter and has better performance in preserving the fine details and

edges while smoothing the noisy image compared to other linear filters such as the Gaussian filter or mean filter. However, the Wiener filter performance is significantly affected by the estimation accuracy of the original image and noise properties.

On the other hand, nonlinear filters [10][11][12] detect and eliminate image pixels that are determined as noise. Nonlinear filters such as the bilateral filter (BL) [12] and the total variation filter (TV) [10] are reported to have superior performance in noise removal and preservation of strong edges. The BL performs spatial averaging by taking a weighted sum of the pixels in a local neighbourhood; the weights depend on both the spatial distance and the intensity distance. The TV searches for the minimal energy functional to reduce the total variation of the image by using a global power constraint. Therefore, the TV reduces the total variation of the noisy image to be as close as possible to the original image. However, the performance of the BL and TV depend significantly on the selection of the filter weight settings, which control the trade-off between the fine details and edges. In many cases, the fine details and textures can be severely oversmoothed. Therefore, despite of extensively proposed denoising methods, developing a technique that could restore a noisy image identical to its original image is still a difficult task.

In this paper, we propose the smooth region's mean deviation-based (SR-MD) denoising method. The main goal of the SR-MD is to preserve the image fine details and edges while effectively reducing the noise level.

The paper is organized as follows. The SR-MD algorithm is described in Section II. A performance comparison of the SR-MD is discussed in Section III. Finally, the concluding remarks are drawn in Section IV.

II. PROPOSED DENOISING METHOD

In this section, we describe the SR-MD, which is performed in the spatial domain. Assume that an original image $y(i, j)$ is corrupted by an additive zero-mean white Gaussian noise $n(i, j)$. The mean ("average", μ) and variance (standard deviation squared, σ^2) are the defining parameters of the AWGN. It has a random value within the distribution and does not depend on the original image intensity [13]. The noisy image, $x(i, j)$, is given by

$$x(i, j) = y(i, j) + n(i, j) \quad (1)$$

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A. SR-MD

The proposed denoising method is performed in a two-phase process. First, the image is restored by reducing noise to a certain level that will still preserve the image fine details and edges. Secondly, the image restored by the first process is further denoised only in the smooth regions to remove remaining noise. We expect to produce a final restored image with effectively reduced noise and well-preserved fine details and edges by utilizing the proposed approach.

In the first process, our main goal is to preserve the fine details and edges as much as possible. Therefore, we seek, around each pixel, the window with the smallest distance to the mean deviation (MD) [14] of the additive noise, MD_r .

For the SR-MD method, we propose the usage of the MD , rather than the variance or standard deviation to estimate the noise distribution. The advantage of the noise estimation by using the MD over the standard deviation is that the MD is actually more efficient than the standard deviation in practical situation [15]. The standard deviation emphasises a larger deviations; by squaring the values makes each unit of distance from the mean exponentially (rather than additively) greater [15]. This will cause overestimation of the noise distribution.

The MD is the mean of the absolute difference between a set of pixel values, $f(i, j)$, with the size of $a \times b$ pixels, and their mean, $\mu_{f(i, j)}$. The MD is defined by

$$MD = \frac{1}{ab} \sum_{i=1}^a \sum_{j=1}^b |f(i, j) - \mu_{f(i, j)}|, \quad (2)$$

where

$$\mu_{f(i, j)} = \frac{1}{ab} \sum_{i=1}^a \sum_{j=1}^b f(i, j). \quad (3)$$

For Gaussian distribution, the standard deviation, σ , can be determined by $1.253 \times MD$.

For each pixel, we utilize an adaptive square window, denoted as $q(i, j)$. $q(i, j)$ should be small enough to preserve the fine details in the image [16]. Therefore, we set the size of $q(i, j)$ to 3×3 pixels. For each $q(i, j)$, we define five different windows, $q_v(i, j)$, surrounding the (i, j) th pixel of the noisy image $x(i, j)$, where $v = 1, 2, \dots, 5$ (see Fig. 1). The windows $q_2(i, j)$ to $q_5(i, j)$ are utilized to detect the fine details and edges more effectively. For each (i, j) th pixel of $x(i, j)$, the mean deviation of each window $q_v(i, j)$ is calculated and denoted as $MD_{q_v(i, j)}$. We compute the distance of each $MD_{q_v(i, j)}$ from MD_r , $d_{MD_{q_v(i, j)}}$, by

$$d_{MD_{q_v(i, j)}} = |MD_{q_v(i, j)} - MD_r|. \quad (4)$$

We find the window $q_v(i, j)$ with the lowest $d_{MD_{q_v(i, j)}}$, (i.e. the closest distance to MD_r), denoted as $q_v(i, j)_{(min)}$. The mean and mean deviation of the window $q_v(i, j)_{(min)}$, $\mu_{q_v(i, j)_{(min)}}$, and $MD_{q_v(i, j)_{(min)}}$, respectively, are employed to restore the (i, j) th

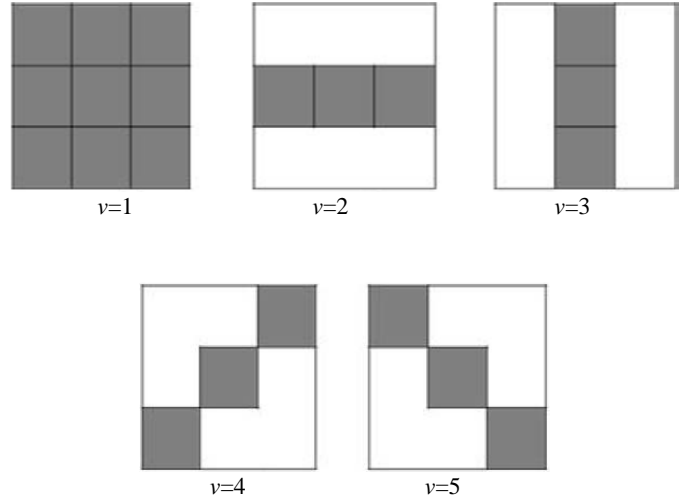


Fig. 1 Adaptive window filter for SR-MD, $q_v(i, j)$

pixel of $x(i, j)$. The restored image, $g(i, j)$, is obtained by

$$\begin{aligned} \text{if } MD_{q_v(i, j)_{(min)}} &\leq (MD_r)^2 \\ g(i, j) &= \mu_{q_v(i, j)_{(min)}} \\ \text{if } MD_{q_v(i, j)_{(min)}} &> (MD_r)^2 \\ g(i, j) &= \begin{cases} z^\ominus & z^\oplus \geq \mu_{q_v(i, j)_{(min)}} \\ z^\oplus & \text{otherwise} \end{cases} \end{aligned}$$

where

$$\begin{aligned} z^\oplus &= \mu_{q_v(i, j)_{(min)}} + MD_{q_v(i, j)_{(min)}} \\ z^\ominus &= \mu_{q_v(i, j)_{(min)}} - MD_{q_v(i, j)_{(min)}}. \end{aligned}$$

(5)

In (5), the $(MD_r)^2$ is utilized as a threshold value. In the noisy environments, especially in high noise level, the noise existence may produce a large deviation among the pixels, which sometimes exceed the MD_r . Therefore, we utilize slightly higher threshold value, $(MD_r)^2$ to divide the smooth and nonsmooth regions.

If the $MD_{q_v(i, j)_{(min)}} \leq (MD_r)^2$, the (i, j) th pixel of the corrupted image $x(i, j)$ is assumed belongs to the smooth region, (i.e. approximates the average value of the (i, j) th pixel of the original image $y(i, j)$). Therefore, the mean $\mu_{q_v(i, j)_{(min)}}$ is assigned to the (i, j) th pixel of $g(i, j)$. If the $MD_{q_v(i, j)_{(min)}} > (MD_r)^2$, the (i, j) th pixel of the corrupted image $x(i, j)$ is assumed belongs to the nonsmooth region. When $\mu_{q_v(i, j)_{(min)}} + MD_{q_v(i, j)_{(min)}} \geq \mu_{q_v(i, j)_{(min)}}$, the (i, j) th pixel value of $x(i, j)$ is assumed to be higher than the (i, j) th pixel value of $y(i, j)$. Thus the $MD_{q_v(i, j)_{(min)}}$ value is subtracted from $\mu_{q_v(i, j)_{(min)}}$ and assigned to the (i, j) th pixel of $g(i, j)$. Otherwise, when $\mu_{q_v(i, j)_{(min)}} +$

$MD_{qv(i,j)(min)} < \mu_{qv(i,j)(min)}$, the (i, j) th pixel value of $x(i, j)$ is assumed to be lower than the (i, j) th pixel value of $y(i, j)$. Hence, the $MD_{qv(i,j)(min)}$ value is added to $\mu_{qv(i,j)(min)}$ and substituted to the (i, j) th pixel of $g(i, j)$.

The second process is to eliminate the remaining noise in the smooth regions of the restored image $g(i, j)$. The window should be large enough to be robust against the noise in the image [16]. Therefore, we utilize a 5×5 square window, $p(i, j)$, centered on (i, j) of the image $g(i, j)$. The mean and mean deviation of this window, denoted as $\mu_{p(i,j)}$ and $MD_{p(i,j)}$, respectively, are employed to restore the output image of the first process, $g(i, j)$.

The final restored image (i.e. estimated original image), $h(i, j)$, is obtained by

$$h(i,j) = \begin{cases} \mu_{p(i,j)} & MD_{p(i,j)} \geq MD_r \\ g(i,j) & \text{otherwise} \end{cases} \quad (6)$$

Since the overall noise in $g(i, j)$ has been reduced, the MD_r is utilized as the threshold value, instead of $(MD_r)^2$. If the $(MD_{p(i,j)} < MD_r)$, the (i, j) th pixel of the final restored image $h(i, j)$ is assumed to belong to the smooth region. Therefore, the mean $\mu_{p(i,j)}$ is assigned to $h(i, j)$. If the $MD_{p(i,j)} \geq MD_r$, the (i, j) th pixel of the final restored image $h(i, j)$ is assumed to belong to the nonsmooth region, and the (i, j) th pixel value of $g(i, j)$ is assigned to $h(i, j)$ (i.e. no denoising is performed).

B. Experiments with the SR-MD

We have conducted experiments on the standard images from the SIDBA database to test the performance of the SR-MD. The images are contaminated by the AWGN with constant and known noise variance, σ^2 . In Fig. 2 we present how the proposed method works in different image patterns for the case $\sigma^2 = 100$.

Fig. 2(a) illustrates the fact that proposed denoising method is well adapted to recovery of the oscillatory patterns. We can observe that the edges are preserved and a certain level of noise has been suppressed.

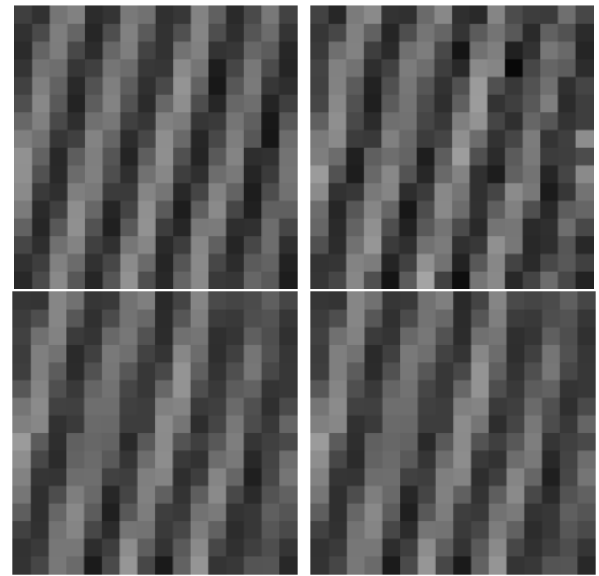
Fig. 2(b) shows the denoising at an edge in a smooth region. Note that the edge has been successfully distinguished from the noise. The edge remains preserved while noise level in the surrounding smooth region is better suppressed.

Due to the nature of this method, the proposed method performs denoising best in the smooth region (see Fig. 2(c)). In the smooth region, there are no significant discontinuity pixel values, leading to effective reduction in this region.

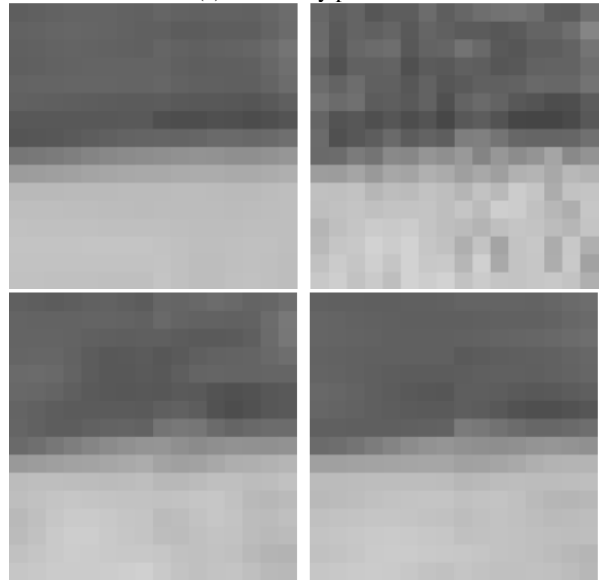
In smooth region with some changes of gradient (see Fig. 2(d)), most of the original smooth region is well reconstructed.

III. RESULTS AND DISCUSSION

In this section, we compare different denoising approaches based on three well-defined criteria: the method noise, visual effect, and objective image quality evaluation of the restored images. Note that every criterion evaluates a different aspect of the denoising method. We have compared our method to the conventional denoising methods: the BL [11] and TV [9].



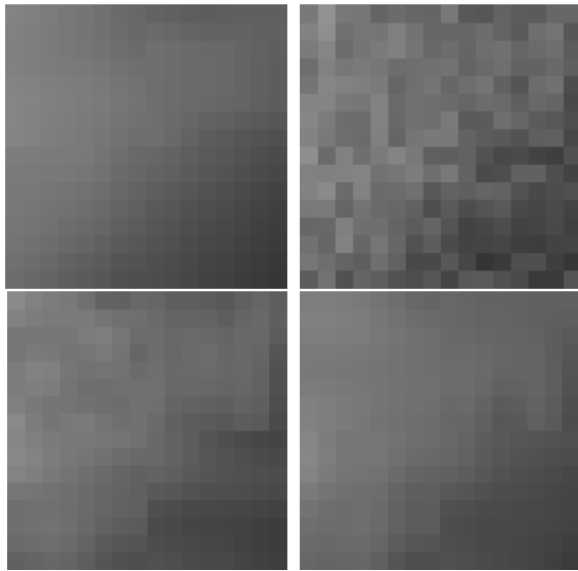
(a) oscillatory patterns



(b) edge in smooth region



(c) smooth region



(d) smooth region with gradient change

Fig. 2 Denoising results by using SR-MD for different image patterns. (Upper left) Original image, (Upper right) Noisy image, (Lower left) $g(i,j)$, (Lower right) $h(i,j)$

Here we assume the noise variance is known (thus, we can calculate the mean deviation from the variance value). Each denoising method for comparison processes the standard images with the same parameters setting (no tuning of parameters was performed (except for noise distribution value) for different noise level or image type). We present the examples of a simulation study using four grayscale standard images (256 x 256) from the SIDBA database: Barbara, Lena, Boat and Woman, which have different image characteristics (see Fig. 3). All images are corrupted with different range of AWGN (noise variance, $\sigma^2 = 25, 100$ and 225).

The method noise is defined as the difference between a noisy image and the restored image. It shows which details are preserved by the denoising process and which are eliminated. The method noise of the restored image $h(i,j)$ is represented by

$$m(i, j) = x(i, j) - h(i, j) \quad (7)$$

where $m(i, j)$ is the method noise (noise estimated by denoising method). In order to preserve as many features as possible of the original image, the method noise should look as much as possible similar to a white noise. Fig. 4 shows the method noise of different methods for Woman with $\sigma^2 = 100$.

The BL modifies most of the image fine details and edges. The TV effectively removes noise in the smooth regions. However some of the strong contrast edges are not well preserved. The proposed method effectively reduces noise in the smooth regions, and also preserves edges with low contrast and most of the strong contrast edges. From the method noise investigation, we found that the proposed method has better fine details and edges preservation relative to the BL and TV.



(a) Barbara



(b) Lena



(c) Boat



(d) Woman

Fig. 3 Standard test images from the SIDBA database

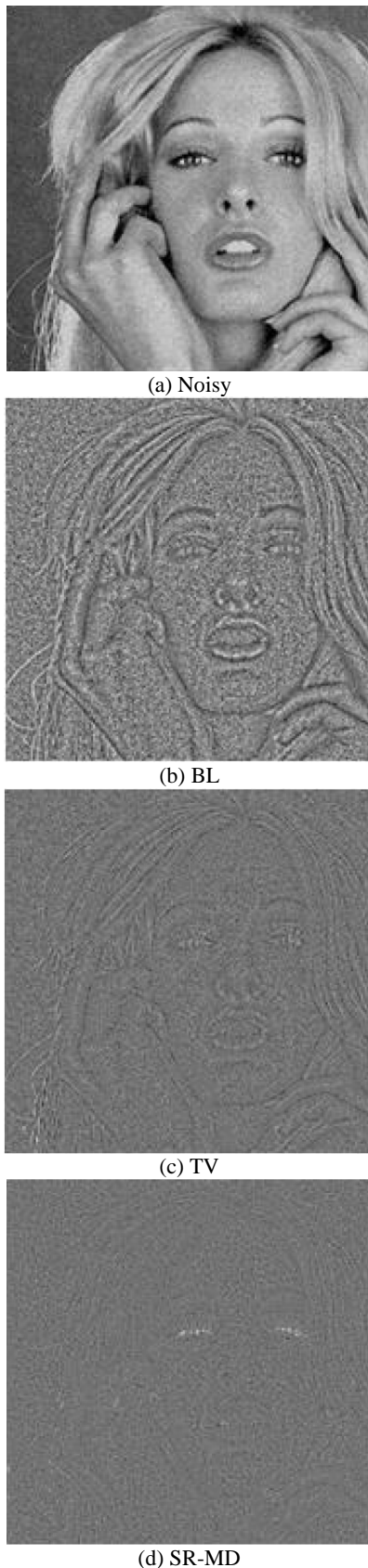


Fig 4 Method noise comparison of Woman image ($\sigma^2 = 100$)

The visual effect of the restored image is another important criterion to evaluate the performance of a denoising algorithm. The objective is to find out the visual quality of the restored image, the effectiveness of the noise suppression, and the reconstruction of the fine details and edges. For the convenience in comparing the visual effects, we illustrate only the results of the restored Barbara image corrupted by different noise levels ($\sigma^2 = 25, 100$ and 225) in Fig. 5, Fig. 6 and Fig. 7, respectively, as well as restored Woman image corrupted by noise level of $\sigma^2 = 225$ in Fig. 8.

From Fig. 5(b), Fig. 6(b), Fig. 7(b) and Fig. 8(b), they show that the BL reduces noise but left additional artifacts in the restored image. Fig. 5(c), Fig. 6(c), Fig. 7(c) and Fig. 8(c) show that the TV results in strong noise removal (for example, the background area) but produces cartoonlike restored image. The TV smooths most of the fine details and edges (for example, the hair details) at the same time. Fig. 5(d), Fig. 6(d), Fig. 7(d) and Fig. 8(d) show that our method reduces a considerable amount of noise and furthermore preserves the fine details and edges better than the BL and TV.

For the objective image quality evaluation, the mean measure of structural similarity (MSSIM) [17] is utilized. The MSSIM aims at mimicking human perception. It models the image distortion as a combination of correlation loss, luminance distortion and contrast distortion. The maximum value for the MSSIM is 1. Therefore, a restored image with the MSSIM value closer to 1 indicates that the estimated restored image is closer to the original image. Let us remark that the MSSIM by itself would not be sufficient, and other quality evaluation criteria are also necessary to evaluate the performance of denoising methods.

Table I shows the performance comparison of different methods in term of MSSIM for different noise levels. The proposed method provides a relatively higher performance when compared with the BL in all images and noise levels. Furthermore, the performance of the proposed method is approximating those of the TV in most cases. In all noise levels, the proposed method has been verified to maintain high MSSIM performance, which is above 0.80.

The investigation validates that the proposed method provides a comparable performance in the fine details and edges preservation compared with the conventional methods. The SR-MD method is simple and utilizes less parameters setting (i.e. noise's MD for threshold and window sizes for $q(i, j)$ and $p(i, j)$, respectively) compared to the TV. The TV performance depends heavily on many parameters settings [10]. Moreover, the SR-MD can perform denoising by using fixed constant parameters (i.e. window sizes) for all noisy images because the threshold value only depends on the noise distribution in each image.



(a) Noisy



(a) Noisy



(b) BL



(b) BL



(c) TV



(c) TV



(d) SR-MD



(d) SR-MD

Fig 5 Restoration comparison of Barbara image ($\sigma^2 = 25$)

Fig 6 Restoration comparison of Barbara image ($\sigma^2 = 100$)



(a) Noisy



(b) BL

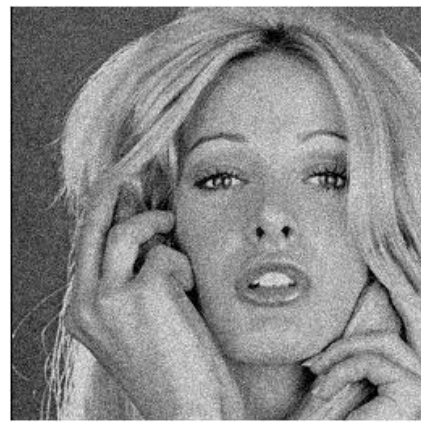


(c) TV



(d) SR-MD

Fig 7 Restoration comparison of Barbara image ($\sigma^2 = 225$)



(a) Noisy



(b) BL



(c) TV



(d) SR-MD

Fig 8 Restoration comparison of Woman image ($\sigma^2 = 225$)

Table I: Performance comparison in MSSIM

Test images	TV	BL	SR-MD
Noise variance, $\sigma^2 = 25$			
Barbara	0.95	0.89	0.94
Lena	0.95	0.91	0.94
Woman	0.94	0.91	0.93
Boat	0.95	0.93	0.94
Noise variance, $\sigma^2 = 100$			
Barbara	0.89	0.87	0.89
Lena	0.90	0.89	0.90
Woman	0.89	0.82	0.88
Boat	0.90	0.84	0.89
Noise variance, $\sigma^2 = 225$			
Barbara	0.82	0.82	0.82
Lena	0.86	0.81	0.86
Woman	0.84	0.75	0.84
Boat	0.85	0.79	0.83

IV. CONCLUSION

From the study, it is found that the proposed method is effective for preserving the image fine details and edges while eliminating the noise.

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REFERENCES

- [1] C. H. Hsieh, P. C. Huang and S. Y. Hung, "Noisy image restoration based on boundary resetting BDND and median filtering with smallest window," *WSEAS Trans. Signal Processing*, vol.1, no.5, pp. 178–187, Jan. 2009.
- [2] V. Gui and C. Căleanu, "On the effectiveness of multiscale mode filters in edge preserving," in *Proc. WSEAS Int. Conf. Systems*, Rodos Island, 2009, pp. 190–195.
- [3] G. Gilboa, N. Sochen, and Y. Zeevi, "Texture preserving variational denoising using an adaptive fidelity term," in *Proc. IEEE Workshop Variational and Level Set Methods in Computer Vision*, Nice, 2003, pp. 137–144.
- [4] A. Buades, B. Coll and J. M. Morel, "A non-local algorithm for image denoising," in *Proc. IEEE Int. Conf. Computer Vision and Pattern Recognition*, San Diego, 2005, vol. 2, pp. 60–65.
- [5] R. Gomathi and S. Selvakumar, "A bivariate shrinkage function for complex dual tree DWT based image denoising," in *Proc. WSEAS Int. Conf. Wavelet Analysis & Multirate Systems*, Bucharest, 2006, pp. 36–40.
- [6] S. Suhaila and T. Shimamura, "Image Restoration Based on Edgemap and Wiener Filter for Preserving Fine Details and Edges," *International Journal Of Circuits, Systems And Signal Processing*, vol. 6, no.5, pp. 618–626, 2011.
- [7] A. D. Hillery and R. T. Chin, "Iterative Wiener filters for image restoration," *IEEE Trans. Signal Processing*, vol. 39, no. 8, pp. 1892–1899, Aug. 1991.
- [8] L. J. van Vliet, I. T. Young and P. W. Verbeek, "Recursive Gaussian derivative filters," in *Proc. IEEE Int. Conf. Pattern Recognition*, Brisbane, 1998, pp. 509–514.
- [9] H. Maitre, *Image processing*, ISTE, London, 2008.
- [10] L. Rudin, S. Osher and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D*, vol. 60, pp. 259–268, Nov. 1992.
- [11] S. M. Smith and J. M. Brady, "SUSAN—A new approach to low level image processing," *International Journal of Computer Vision*, vol. 23, no. 1, pp. 34–39, 45–78, May 1997.
- [12] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *Proc. IEEE Int. Conf. Computer Vision*, Bombay, 1998, pp. 839–846.
- [13] R. C. Gonzalez, R. E. Woods and S. L. Eddins, *Digital Image Processing using MATLAB*. Prentice Hall, New Jersey, 2004.
- [14] J. F. Kenney and E. S. Keeping, *Mathematics of Statistics*. Princeton, New Jersey, 1962.
- [15] S. Gorard, "Revisiting a 90-year-old debate: the advantages of the mean deviation," *British Journal of Educational Studies*, vol. 53, no. 4, pp. 417–430, Dec. 2005.
- [16] L. He, and I. R. Greenshields, "A nonlocal maximum likelihood estimation method for Rician noise reduction in MR images," *IEEE Trans. Medical Imaging*, vol. 28, no. 2, pp. 165–172, Feb. 2009.
- [17] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Trans. Image Processing*, vol. 13, no. 4, pp. 600–612, Apr. 2004.

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