International Refereed Journal of Engineering and Science (IRJES)
ISSN (Online) 2319-183X, (Print) 2319-1821
Volume 5, Issue 8 (August 2016), PP.24-28

Robust Image Denoising Using Infantile Fixation of Non Local Euclidean Median in Patch Space

Gopala Krishna Nagasarapu, Dr.A.Senthil Rajan

Abstract: Denoising digital images is a pre-process method in any application such as satellite, medical, remote sensing, face recognition and bio-metric authentication etc. Here in this proposal, we implemented a novel image denoising scheme using infantile fixation of non-local patch (IF-NLP), which is an extension version for the classical non local means (NLM), non-localEuclidean median (NLEM), generalized NLM and even fast-NLM algorithm. The proposed algorithm utilizes the patch reorganization lopping of pixels for denoising noisy or corrupted pixels. It has tested with larger noise variances. Simulation results have shown that the proposed denoising model has performed superior to the existing denoising models in terms of peak signal to noise ratio (PSNR), mean square error (MSE).
Indexterms: denoising, NLM, G-NLM, F-NLM, Non-local patch, PSNR and MSE.

I. INTRODUCTION

In many applications, while transmitting the images and/or acquiring an image from both digital cameras will be affected with few or more amount of the noise from a variety of sources. Further processing of these noisy images can be done only after removal of this random noise, because this type of noise elements will create some serious issues in practical applications such as satellite, bio-medical, computer vision, remote sensing, artistic work or marketing and also in many fields. Denoising an image is a primary problem in the applications of image processing. Denoising is a pre-process technique in many applications for improving the quality of digital images without losing its original information. It plays an important role in object identification, face tracking, tumour segmentation and image retrieval etc. Estimating an original image from the corrupted or sparse image by preserving its edge, texture and structural details is very important. In order to remove the noise from images, prior knowledge about the noise distribution plays a vital role. Mainly, there are two types of noises like impulse noise (IN), additive white Gaussian noise (AWGN). Due to the electrons thermal motion in camera sensors and circuits, AWGN will be introduced. In general, when there is a very small change in original pixel value that is known as Gaussian noise. Histogram is a graphical representation of image, which plots a discrete graph of the distortion amount of the pixel values at which frequency it exists, and shows a normal distribution of noise. IN is often introduced due to improper functioning of camera sensors, hardware impairment memory locations or bit errors in transmission.Median filters [1] have been used dominantly to remove IN. Many improvements have been done in median filters to enhance the performance and to preserve the local structures [2-10], which includes weighted median filter (WMF) [3], multistate median filter (MMF) [4] and centre weighted median filter (CWMF) [3].

All of them do not recognize that the present pixel is noisy or not and they tend to over smooth the denoised image. Hence, based on this concept several filters have been proposed in the literature such as switching median filter (SMF) [5], adaptive median filter (AMF) [6], tristate median filter (TMF) [7], adaptive CWMF [8], conditional signal AMF [9] and directional WMF [10] etc.Bilateral filter (BF) [12] is a well-known nonlinear filter, which preserves the information about the edges. An extension for the BF is non-local means (NLM) filtering algorithm [15]. BM3D approach has been proposed in [14] by combining the similar non local patches into a 3D cube and applying transform based shrinkage. Then after, LPG-PCA has been proposed in [16]. The work proposed in [?] initiates the generalized NLM to remove the AWGN and denoise the corrupted images. It was recently demonstrated in [13] that the denoising performance of NLM can be improved at large noise levels by replacing the mean with the robust Euclidean median. However, all the above mentioned denoising algorithms were suffering from lack of stability and efficiency. Here, a novel algorithm for noise removal from corrupted digital images has been proposed by using IF-NLP to improve the denoise system performance in terms of quality metrics.

II. LITERATURE REVIEW

Many researchers have developed and published enough papers on removing or eliminating either IN or AWGN [12-20], however these methods were not supposed to remove the AWGN and IN. From the past decades, several algorithms have been proposed [22-36] to remove the noise which occurs due to noise from multiple sources.Median filters [1] have been used dominantly to remove IN. However, median filters have been suffering from few shortcomings i.e., it does not preserve the edges information and destroys the local structures of image, which in results that the denoised images looks unnatural. When IN density is very high then this problem will become more serious. To solve these issues, many improvements have been done in median filters to enhance the performance and to preserve the local structures [2-10], which includes weighted median filter (WMF) [3], multistate median filter (MMF) [4] and centre weighted median filter (CWMF) [3]. All of them do not recognize that the present pixel is noisy or not and they tend to over smooth the denoised image. Hence, one possible way is to detect or identify the IN corrupted pixels and leave the uncorrupted pixels as it is. Based on this concept several filters have been proposed in the literature such as switching median filter (SMF) [5], adaptive median filter (AMF) [6], tristate median filter (TMF) [7], adaptive CWMF [8], conditional signal AMF [9] and directional WMF [10] etc.

In image denoising literature, AWGN is a most widely studied noise model [12-20]. Conventional linear filtering schemes such as Gaussian filtering has been used to filer the noisy images those are corrupted by AWGN. But, it will over smooth the edges while removing the noise. To address this issue, nonlinear filtering schemes have been developed in further years. Bilateral filter (BF) [12] is a well-known nonlinear filter, which preserves the information about the edges by estimating the denoised pixel as the neighbouring pixels weighted average, but the weights are influenced by spatial and intensity similarity. An extension for the BF is non-local means (NLM) filtering algorithm [15], in which the denoised pixel is estimated as the weighted average of the all its standardized pixels of an original image and these weights are influenced by the similarity between them. BM3D approach has been proposed in [14] by combining the similar non local patches into a 3D cube and applying transform based shrinkage. Then after, by using these similar patches and grouping those into a matrix then applied principle component analysis (PCA) to denoise the AWGN image, which is known as LPG-PCA and it has been proposed in [16]. In recent years, an attractive attention has been made in image restoration and denoising algorithms by introducing dictionary learning and sparse representation schemes. The work proposed in [13] initiates the dictionary learning from natural images to remove the AWGN and denoise the corrupted image using k- singular value decomposition (K-SVD). In [17], the author has proposed the use of both sparse representation and nonlocal self-similarity (NSS) regularization to remove the AWGN.

However, the AWGN and IN increases the difficulties and makes much more complex to denoise the images. Very few methods have been developed in the literature to remove this noise [22-26]. Author in [24] proposed a noise removal algorithm using median based signal dependent rank ordered mean (SDROM), but it produces bitter artifacts often. IN detection has been done by integrating the trilateral filter (TF) [27] with absolute difference of rank order (ROAD) statistics into the BF [12]. Switching BF [28] is a method of detection and replacement, which is also a modification to the BF. To decide the present pixel is a noisy or not, it computes the reference median. If the reference median and target pixel difference is large then the target pixel is a noise pixel and therefore mixed noise is eliminated by switching between AWGN and IN. A method that is known as a two-phase method to restore the noisy images which were corrupted by mixed noise. Later on it has been improved and republished to increase the efficiency of denoised system. Xiao et al. proposed an $l_1 - l_0$ minimization method, it achieves good denoising performance but it has been suffering from higher computational complexity. A total variation (TV) regularization method has been proposed to reduce the computational complexity by aiming in mixed noise removal with a cost functional consisting of regularization data fidelity terms l_2 and l_1. Dong et al. proposed a new frame work for denoising an image by introducing a new variable to comprise the outliers. Meanwhile, this term used as a regularizer by considering that the amount of damaged pixels by IN is very small. More recently, a method which incorporates both sparse coding and learning of dictionary, reconstructing an image, noise clustering and estimating the parameters into a four step framework by solving a minimization problem.Gopala Krishna Nagasarapu and A. SenthilRajan in [30], proposed a generalized NLM scheme with block based PCA algorithm, which has performed far better over classical NLM, fast NLM and wavelet thresholdingbased NLM (WT-NLM). It was recently demonstrated that the performance of NLM can be improved at large noise levels by replacing the mean by the stronger Euclidean median. The Euclidean mean and median can be put into common a frame work of infantile fixation, in which first we consider the residuals of l_2-norm minimization method and later l_1-norm residuals. Here, in this we investigated the problem of l_p i.e., what happens if the range of p is $0 < p < 1$, which is known as patch space.

III. PROPOSED ALGORITHM

A. Non-Local Euclidean Median

To set up notations, we recall the NLM working. Let $m = (m_i)$ be some input noisy image index. The standard setting is that m is the clean image I corrupted version,

$$m_i = I_i + \sigma v_i \qquad (1)$$

Where σ is a noise variance and v_i is $i.i.d\mathcal{N}(0,1)$, our goal is to estimate a noise free image from the given noisy measurement. In, NLM the restored image $\widehat{m}_i$ is computed using,

$$\widehat{m}_i = \frac{\sum_{j\epsilon N\,(i)} w_{ij}\, m_i}{\sum_{j\epsilon N\,(i)} w_{ij}} \qquad (2)$$

Where w_{ij} is the weight assigned to pixels, here $N(i)$is the $i-th$pixel neighbourhood over which the averaging is performed. In practice, however, one can restrict$N(i)$ to a geometric neighbourhood. The other idea of NLM is to set weights using image patches centred around each pixel. Let k be the length of window. In practice, the weights of NLM will be calculated as,

$$w_{ij} = \exp\left(-\frac{1}{h^2}\|P_i - P_j\|^2\right) \qquad (3)$$

Where $\|P_i - P_j\|$ is the Euclidean distance and $h$is a smoothing parameter. $P_i$denotes the restriction of m to a square window around i.

It has demonstrated in [27], that the performance of NLM denoising can be improved by replacing the infantile fixation of l_2 with the more stronger l_1-infantile fixation. More, precisely, given weights w_{ij}, note that (2) is equivalent to performing the following, on the patch space:

$$\hat{P}_i = \arg\min_P \sum_{j\epsilon N(i)} w_{ij} \|P - P_j\|^2 \qquad (4)$$

And then setting $\hat{m}_i$to be the center pixel in $\hat{P}_i$. Surely, it reduces to (2) once we write the infantile fixation in terms of the center pixel $\hat{m}_i$. The idea in [27] was to use l_1-infantile fixation instead, namely, to compute

$$\hat{P}_i = \arg\min_P \sum_{j\epsilon N(i)} w_{ij} \|P - P_j\| \qquad (5)$$

and then set $\hat{m}_i$to be the center pixel in $\hat{P}_i$. Note that (5) is a convex optimization, and the minimizer is unique when k>1 [28], which in results NLEM. It was demonstrated that NLEM performed far better than NLM on a large class of natural and synthetic images with larger noise levels which is above a certain threshold. More importantly, it has shown that the improvement in NLEM came from pixels located close to edges. An inlier-outlier model of patch space was proposed and the robustness of (5) has improved in the presence of outliers.

B. Infantile fixation of NLEMin patchspace

It was well known that $l_1$minimization is much stronger to outliers than l_2-minimization. A simple argument is that the residuals which are unsquared$\|P - P_j\|$in (5) are better guarded against the deviated data points compared to the residuals that are squared$\|P - P_j\|^2$. Here in this, we proposed an infantile fixation point that could be varied based on the suppression of residuals.

$$\hat{P}_i = \arg\min_P \sum_{j\epsilon N(i)} w_{ij} \|P - P_j\|^p \qquad (6)$$

The visceral idea of the proposed algorithm is that, we can better suppress the residuals $\|P - P_j\|$ induced by outliers, by taking the smaller values of p. This will make the infantile fixation very robust to outliers that are compared with$p = 1$. Therefore, we can refer that (6) is a infantile fixation of non-local patch (IF-NLP), where the values of p will lies between (0,2]. To optimize the (6), we should have an iterative solver that regularizes the proposed algorithm. The working of this regularization is as follows:

First, we set

$$P^{(0)} = \frac{\sum_{j\epsilon N(i)} w_{ij} P_j}{\sum_{j\epsilon N(i)} w_{ij}} \qquad (7)$$

Then at every iteration$k \geq 1$, we can write $\|P - P_j\|^p = \|P - P_j\|^2 . \|P - P_j\|^{p-2}$in (6), use the current estimate to approximate this by$\|P - P_j\|^2 . \|P^{(t-1)} - P_j\|^{p-2}$, which in results the alternate least squares problem, given by

$$P^{(t)} = \arg\min_P \sum_{j\epsilon N(i)} w_{ij} \frac{\|P - P_j\|^2}{\left(\|P^{(t-1)} - P_j\|^2 + e^{(t)}\right)^{1-p/2}} \qquad (8)$$

IV. SIMULATION RESULTS

To demonstrate the performance of proposed algorithm, here in this section we had presented some experimental results on natural and synthetic images, which has been done in MATLAB 2014a version with 4GB RAM and i3 processor. The experiments have beenconducted on various images of size 256x256 and 512x512, which is corrupted by large noise levels i.e., sigma = 25 dB to 100 dB. This corrupted images have been denoised by using NLM, NLEM and proposed IF-NLP with various $p$values i.e., the range is (0,2]. The results which have been shown in fig.1, show that the proposed technique is significantly effective than the other techniques in terms of visual perceptual quality.

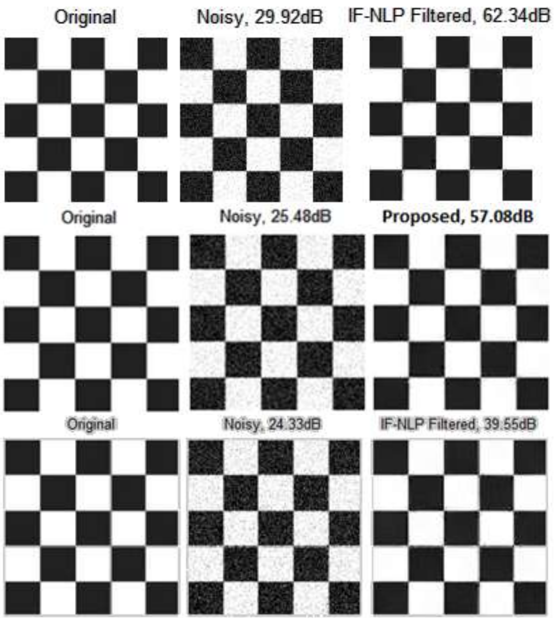

Fig.1 original, noisy, denoised using NLM and proposed algorithms with sigma= 15dB, 25 dB, 30dB

V. CONCLUSIONS

In this, we introduced a novel image denoising scheme based on infantile fixation of NLEM in patch space, which has produced excellent PSNR values at larger noise levels. It also compared with the existing fast NLM filter, classical NLM filter and also with the generalized NLM. Furthermore, It can be modified by developing probable conditions for the value of patch selection *p.*

REFERENCES

[1]. Pitas and A. N. Venetsanopoulos, Nonlinear Digital Filters: Principles and Applications. Norwell, MA: Kluwer, 1990.

[2]. Brownrigg, "The weighted median filter," Commun. ACM, vol. 27, no. 8, pp. 807-818, Aug. 1984.

[3]. S. J. Ko and Y. H. Lee, "Center weighted median filters and their applications to image enhancement" IEEE Trans. Circuits syst., vol. 38, no. 9, pp. 984-993, Sep. 1991.
Nieminen, P. Heinonen, and Y. Neuvo, "A new class of detail preserving filters for image processing," IEEE. Trans. Pattern Anal. Mach. Intell., vol. PAMI-9, no. 1, pp. 74-90, Jan. 1987.

[4]. T. Sun and Y. Neuvo, "Detail-preserving median based filters in image processing," Pattern Recognit. Lett., vol. 15, no. 4, pp. 341-347,Apr.1994.

[5]. H. Hwang and R. A. Haddad, "Adaptive median filters: New algorithm and results," IEEE Trans. Image Process., vol. 4, no. 4, pp. 499-502, Apr. 1995.

[6]. T. Chen, K. K. Ma, and L. H. Chen, "Tri-state median filter for image denoising," IEEE Trans. Image Process., vol. 8, no. 12, pp. 1834-1838, Dec.1999.

[7]. T. Chen and H. R. Wu, "Adaptive impulse detection using center weighted median filters," IEEE Signal Process. Lett., vol. 8, no. 1, pp.13, Jan. 2001.

[8]. G. Pok, J. C. Liu, and A. S. Nair, "Selective removal of impulse noise based on homogeneity level information," IEEE Trans. Image Process., vol. 12, no. 1, pp. 85-92, Jan. 2003.

[9]. Y. Q. Dong and S. F. Xu, "A new directional weighted median filter for removal of random-valued impulse noise," IEEE Signal Process. Lett., vol. 14, no. 3, pp. 193-196, Mar. 2007.

[10]. N. I. Petrovic and V. Crnojevic, "Universal impulse noise filter based on genetic programming," IEEE Trans. Image Process., vol. 17, no. 7, pp. 1109-1120, Jul. 2008.

[11]. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in Proc. IEEE Int. Conf. Computer Vision, 1998, pp. 839-846.

[12]. M. Aharon, M. Elad, and A.M. Bruckstein, "K-SVD: An algorithm for designing of overcomplete dictionaries for sparse representation," IEEE Trans. Signal Processing., vol. 54, no. 11, pp. 4311-4322, Nov. 2006.

[13]. K. Dabov, A. Foi, V. Katkovnik, and K.Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative Filtering," IEEE Trans. Image Process., vol. 16, no. 8, pp. 2080-2095, Aug. 2007.
Buades, B. Coll, and J. M. Morel, "A review of image denoising methods, with a new one," Multiscale Model. Simul., vol. 4, no.2, pp. 490-530, 2005.

[14]. L. Zhang, W. S. Dong, D. Zhang, and G. M. Shi, "Two-stage image denoising by principal component analysis with local pixel grouping," Pattern Recognit., vol. 43, no. 4, pp. 1531-1549, Apr. 2010.
[15]. W. S. Dong, L. Zhang, G. M. Shi, and X. Li, "Nonlocally Centralized s- parse representation for image restoration," IEEE Trans. Image Process., vol. 22, no. 4, pp. 1620-1630, Apr. 2013.
[16]. H. Burger, C. Schuler, and S. Harmeling, "Image denoising: can plain neural networks compete with BM3D," in Proc. Int. Conf. Compu. Vis. Pattern Recognit., 2012, pp. 2392-2399.
[17]. W. Dong, X. Li, L. Zhang and G. Shi, "Sparsity-based image denoising via dictionary learning and structural clustering," in Proc. Int. Conf. Compu. Vis. Pattern Recognit., 2011, pp. 457-464.
Buades, B. Coll, and J. M. Morel, "A non-local algorithm for image denoising," in Proc. Conf. Comput. Vis. Pattern Recognit., 2005, pp.60- 65.
[18]. L. Zhang, L. Zhang, X. Mou and D. Zhang, "FSIM: A Feature similarity index for image quality assessment," IEEE Trans. Image Process., vol. 20, no. 8, pp. 2378- 2386, Aug. 2011.
[19]. R. Li and Y. J. Zhang, "A hybrid filter for the cancellation of mixed Gaussian noise and impulse noise," in IEEE. Int. Conf. Information. Communications. and Signal Processing, 2003, pp. 508-512.
[20]. M. Yan, "Restoration of images corrupted by impulse noise and mixed Gaussian impulse noise using blind in painting," SIAM Journal on Imaging Science., vol. 6, no. 3, pp. 1227-1245, 2013.
[21]. 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.
[22]. S. Peng and L. Lucke, "Multi-level adaptive fuzzy filter for mixed noise removal," in Proc. IEEE Int. Symp. Circuits Systems, Seattle, WA, Apr. 1995, vol. 2, pp. 1524-1527.
[23]. Lopez-Rubio, "Restoration of images corrupted by Gaussian and uniform impulsive noise," Pattern Recognit., vol. 43, no. 5, pp. 1835- 1846, May. 2010.
[24]. K. N. Chaudhury, A. Singer, "Non-local Euclidean medians," IEEE Signal Processing Letters, vol. 19, no. 11, pp. 745 - 748, 2012.
[25]. P. Milasevic, G. R. Ducharme, "Uniqueness of the Spatial Median", Annals of Statistics, vol. 15, no. 3, 1332-1333, 1987.
[26]. Lerman, M. McCoy, J. A. Tropp, T. Zhang, "Robust computation of linear models, or how to find a needle in a haystack," arXiv:1202.4044 [cs.IT].
[27]. GopalakrishnaNagasarapu, Dr. A. SenthilRajan, "Generalized Non-Local mean algorithm for De-speckling of digital images with Classical NLM and Wavelet Transform", International Journal of Emerging Trends in Science and Technology (IJETST), Vol. 2 , No. 8, pp. 3077-3082, 2015.

About the Author(s):
Gopala Krishna Nagasarapu
Working as Head of the Department, CSE, PNC& VIET,Repudi, Guntur Dist, Andhra Pradesh, India-9849803585
Research Scholar, Dept of CSE, ALAGAPPA UNIVERSITY, Tamilnadu, INDIA
Dr.A.Senthil Rajan
Director, Computer Center, Alagappauniversity,Karaikuddi, Tamilnadu, India