Image Denoising Methods: An Analytical Study from Classical to State-of-the-Art Technologies

Dheeraj Kumar Chaturvedi[1]
Department of Electronics and Communication Engineering
Technocrat Institute of Technology
Bhopal, MP, India

Saima Khan[2]
Department of Electronics and Communication Engineering
Technocrat Institute of Technology
Bhopal, MP, India

* Corresponding Author: Dheeraj Kumar Chaturvedi

Abstract: *With the explosion in the quantity of advanced pictures required each day, the interest for more precise and outwardly satisfying pictures is expanding. Be that as it may, the pictures caught by present day cameras are definitely debased by commotion, which prompts decayed visual picture quality. Along these lines, work is needed to lessen commotion without losing picture highlights (edges, corners, and other sharp constructions). Up until this point, analysts have effectively proposed different techniques for diminishing commotion. Every strategy has its own benefits and inconveniences. In this paper, we sum up some significant exploration in the field of picture denoising. To begin with, we give the plan of the picture denoising issue, and afterward we present a few picture denoising methods. Likewise, we examine the attributes of these procedures. At long last, we give a few promising bearings to future exploration.*

Keywords: *Image denoising, Non-local means, Sparse representation, Low-rank, Convolutional neural network.*

I. INTRODUCTION

Inferable from the impact of climate, transmission channel, and different components, pictures are unavoidably discolored by appeal during securing, pressure, and transmission, prompting twisting and loss of picture data. With the presence of commotion, conceivable ensuing picture preparing undertakings, for example, video handling, picture investigation, and following, are antagonistically influenced. In this manner, picture denoising assumes a significant part in present day picture handling frameworks[1]. Picture denoising is to eliminate commotion from a boisterous picture, in order to reestablish the genuine picture. In any case, since commotion, edge, and surface are high recurrence parts, it is hard to recognize them during the time spent denoising and the denoised pictures could unavoidably lose a few subtleties. By and large, recuperating significant data from boisterous pictures during the time spent commotion evacuation to acquire great pictures is a significant issue these days. Truth be told, picture denoising is an exemplary issue and has been read for quite a while. In any case, it stays a difficult and open assignment [2]. The principle justification this is that from a numerical point of view, picture denoising is a converse issue and its answer isn't remarkable. In ongoing many years, incredible accomplishments have been made nearby picture denoising, and they are checked on in the accompanying segments[3]. The rest of this paper is coordinated as follows. In Section "Picture denoising issue proclamation", we give the plan of the picture denoising issue. Areas "Old style denoising strategy, Transform procedures in picture denoising, CNN-based denoising strategies" sum up the denoising methods proposed up to now [4]. Area "Analyses" presents broad tests and conversation. Ends and some potential bearings for future examination are introduced in Section "Ends". Picture denoising issue explanation Mathematically, the issue of picture denoising can be demonstrated as follows:

$$Y = x + n \qquad \text{(i)}$$

Where, Y is the noticed uproarious picture, x is the obscure clean picture, and n addresses added substance white Gaussian clamor (AWGN) with standard deviation σn, which can be assessed in commonsense applications by different techniques, for example, middle supreme deviation [5], block-based assessment [6], and guideline segment investigation (PCA)- based strategies [7]. The reason for clamor decrease is to diminish the commotion in characteristic pictures while limiting the deficiency of unique highlights and improving the sign to-commotion proportion (SNR). The significant difficulties for picture denoising are as per the following:

- flat zones ought to be smooth,
- edges ought to be ensured without obscuring,
- textures ought to be safeguarded, and
- new relics ought not be produced.

Owing to solve the clean image x from the eq. (i) is an ill-posed problem, we cannot get the unique solution from the image model with noise. To obtain a good estimation image $\hat{x}$, image denoising has been well-studied in the field of image processing over the past several years. Generally, image denoising methods can be roughly classified as [3]: spatial domain methods, transform domain methods, which are introduced in more detail in the next couple of sections.

II. CLASSICAL DENOISING METHOD

Spatial area techniques plan to eliminate commotion by computing the dark estimation of every pixel dependent on the relationship between's pixels/picture patches in the first picture. All in all, spatial space strategies can be partitioned into two classifications: spatial area separating and variational denoising techniques.

Spatial space separating

Since sifting is a significant method for picture preparing, countless spatial channels have been applied to picture denoising, which can be additionally arranged into two sorts: straight channels and non-direct channels. Initially, direct channels were received to eliminate commotion in the spatial area, however they neglect to protect picture surfaces. Mean sifting has been embraced for Gaussian commotion decrease, nonetheless, it can over-smooth pictures with high demand [8][9].

To beat this burden, Wiener sifting has additionally been utilized, yet it likewise can undoubtedly obscure sharp edges. By utilizing non-direct channels, for example, middle sifting and weighted middle separating, commotion can be stifled with no distinguishing proof. As a non-direct, edge-saving, and commotion diminishing smoothing channel, Bilateral sifting is generally utilized for picture denoising. The power estimation of every pixel is supplanted with a weighted normal of force esteems from close by pixels. One issue concerning the reciprocal channel is its effectiveness [10].

The savage power execution takes O (Nr 2) time, which is restrictively high when the portion range r is huge. Spatial channels utilize low pass separating on pixel bunches with the explanation that the clamor involves a higher area of the recurrence range. Ordinarily, spatial channels dispense with clamor to a sensible degree yet at the expense of picture obscuring, which thusly loses sharp edges.

Vibrational denoising methods

Existing denoising methods use image priors and minimize an energy function E to calculate the denoised image $\hat{x}$. First, we obtain a function E from a noisy image y, and then a low number is corresponded to a noise-free image through a mapping procedure[11][12]. Then, we can determine a denoised image $\hat{x}$ by minimizing E:

$$\hat{x} \in \arg \text{minx}\ E(x) \qquad \text{(ii)}$$

The motivation for variational denoising methods of Eq. (iii) is maximum a posterior (MAP) probability estimate. From a Bayesian perspective, the MAP probability estimate of x is

$$\hat{x} \in \arg\max P\{x|y\} = \arg\max \frac{P\{x|y\}}{P(y)} P(x) \qquad \text{(iii)}$$

which can be equivalently formulated as

$$\hat{x} = \arg\max \log P\{x|y\} + \log P(x) \qquad \text{(iv)}$$

Transform techniques in image denoising

Picture denoising techniques have continuously evolved from the underlying spatial area strategies to the present change space strategies. At first, change space techniques were created from the Fourier change, however from that point forward, an assortment of change area strategies slowly arose, for example, cosine change, wavelet area techniques, and block-coordinating and 3D separating (BM3D)[13]. Change area strategies utilize the accompanying perception: the attributes of picture data and commotion are distinctive in the change space.

Change space separating strategies

Interestingly with spatial area sifting techniques, change space separating strategies initially change the given boisterous picture to another space, and afterward they apply a denoising strategy on the changed picture as indicated by the various attributes of the picture and its commotion (bigger coefficients signify the high recurrence part, i.e., the subtleties or edges of the picture, more modest coefficients mean the clamor) [14]. The change space sifting techniques can be partitioned by the picked premise change capacities, which might be information versatile or non-information versatile.

Information versatile change

Independent part examination (ICA) and PCA capacities are embraced as the change apparatuses on the given boisterous pictures. Among them, the ICA strategy has been effectively executed for denoising non-Gaussian information. These two sorts of techniques are information versatile, and the presumptions on the distinction between the picture clamor actually hold [15]. Be that as it may, their fundamental disadvantage is high-computational expense since they utilize sliding windows and require an example of clamor free information or possibly two picture outlines from a similar scene.

In any case, in certain applications, it very well may be hard to get clamor free preparing information. Non-information versatile change The non-information versatile change area sifting techniques can be additionally partitioned into two areas, in particular spatial-recurrence space and wavelet area. Spatial-recurrence area separating techniques utilize low pass sifting by planning a recurrence space channel that passes all frequencies lower than and lessens all frequencies higher than a cut-off recurrence [16][17]. All in all, subsequent to being changed by low-pass channels, for example, Fourier change, picture data chiefly spreads in the low recurrence area, while commotion spreads in the high recurrence space [18]. Along these lines, we can eliminate clamor by choosing explicit change area includes and changing them back to the picture space. In any case, these strategies are tedious and rely upon the cut-off recurrence and channel work conduct. As the most researched change in denoising, the wavelet change disintegrates the info information into a scale-space portrayal. It has been demonstrated that wavelets can effectively eliminate clamor while saving the picture qualities, paying little heed to its recurrence content. Like spatial area separating, sifting activities in the wavelet space can likewise be partitioned into straight and non-direct strategies [19]. Since the wavelet change has numerous great qualities, like meager condition and multi-scale, it is as yet a functioning region of exploration in picture denoising. Be that as it may, the wavelet change vigorously depends on the determination of wavelet bases. On the off chance that the determination is wrong, picture appeared in the wavelet space can't be very much addressed, which causes poor denoising impact. Consequently, this technique isn't versatile [20].

BM3D

As a compelling and incredible expansion of the NLM approach, BM3D, which was proposed by Dabov et al., is the most mainstream denoising technique. BM3D is a two phase non-locally community oriented sifting strategy in the change space. In this strategy, comparable patches are stacked into 3D gatherings by block coordinating, and the 3D gatherings are changed into the wavelet area. At that point, hard thresholding or Wiener separating with coefficients is utilized in the wavelet area. At long last, after a reverse change of coefficients, all assessed patches are amassed to remake the entire picture. In any case, when the commotion increments continuously, the denoising execution of BM3D diminishes significantly and antiques are presented, particularly in level territories[21]. To improve denoising execution, many improved forms of BM3D have seemed. For instance, Maggioni et al. as of late proposed the square coordinating and 4D separating (BM4D) technique, which is an expansion of BM3D to volumetric information. It uses solid shapes of voxels, which are stacked into a 4-D gathering[22]. The 4-D change applied on the gathering all the while abuses the nearby relationship and non-neighborhood connection of voxels. Along these lines, the range of the gathering is exceptionally inadequate, prompting successful division of sign and clamor through coefficient shrinkage.

III. CNN-BASED DENOISING METHODS

As a rule, the tackling techniques for the target work in Eq. expand upon the picture debasement measure and the picture priors, and it tends to be separated into two principle classifications: model-based improvement strategies and convolutional neural organization (CNN)- based techniques. The variational denoising strategies talked about above have a place with model-based improvement plans, which discover ideal answers for remake the denoised picture. Notwithstanding, such strategies ordinarily include tedious iterative derivation[23]. Despite what might be expected, the CNN-based denoising techniques endeavor to become familiar with a planning capacity by streamlining a misfortune work on a preparation set that contains debased clean picture sets. As of late, CNN-based strategies have been grown quickly and have performed well in some low-level PC vision undertakings. The utilization of a CNN for picture denoising can be followed back to, where a five-layer network was created. Lately, numerous CNN-based denoising techniques have been proposed. Contrasted with that of ref., the presentation of these strategies has been extraordinarily improved. Besides, CNN-based denoising techniques can be partitioned into two classifications: multi-facet insight (MLP) models and profound learning strategies.

MLP models

MLP-based picture denoising models incorporate auto encoders proposed by Vincent et al. and Xie et al. Chen et al.proposed a feed-forward profound organization called the teachable non-straight response dissemination (TNRD) model, which accomplished a superior denoising impact. This classification of techniques has a few benefits [24]. To begin with, these techniques work effectively inferable from less ratiocination steps. Besides, on the grounds that enhancement calculation can determine the discriminative engineering, these techniques have better interpretability. All things considered, interpretability can build the expense of execution; for instance, the MAP model limits the learned priors and surmising strategy [25]. Profound learning-based denoising strategies The best in class profound picking up denoising techniques are ordinarily founded on CNNs. The overall model for profound learning-based denoising strategies is defined as

$$\min \Theta \text{ loss } (\hat{x}, x) = F(y, \sigma; \Theta) \qquad \text{(v)}$$

where F(·) signifies a CNN with boundary set Θ, and loss(·) indicates the misfortune work. loss(·) is utilized to assess the vicinity between the denoised picture $\hat{x}$ & the ground-truth x. Inferable from their remarkable denoising capacity, significant consideration has been centered around profound learning-based denoising techniques. Zhang et al. presented remaining learning and cluster normalization into picture denoising interestingly; they additionally proposed feed-forward denoising CNNs (DnCNNs). There are two primary qualities of DnCNNs: the model applies a leftover learning definition to get familiar with a planning capacity, and it joins it with bunch standardization to speed up the preparation system while improving the denoising results. In particular, incidentally, lingering learning and bunch standardization can profit one another, and their combination is viable in accelerating the preparation and boosting denoising execution. Albeit a prepared DnCNN can likewise deal with pressure and interjection mistakes, the prepared model under σ isn't appropriate for other commotion changes[26][27]. At the point when the commotion level σ is obscure, the denoising technique should empower the client to adaptively make a compromise between clamor concealment and surface security [28]. The quick and adaptable denoising convolutional neural organization (FFDNet) was acquainted with fulfill these attractive qualities. For FFDNet, M shows an information while the boundary set Θ are fixed for commotion level. Another significant commitment is that FFDNet follows up on down-inspected sub-pictures, which speeds up the preparation and testing and furthermore extends the responsive field. Accordingly, FFDNet is very adaptable to various commotions. Albeit this technique is successful and has a short running time, the time intricacy of the learning interaction is high[29]. The improvement of CNN-based denoising techniques has upgraded the learning of significant level highlights by utilizing a progressive organization.

IV. COMPARISON METHODS

A comprehensive evaluation is conducted on several state-of-the-art methods, including Wiener filtering, Bilateral filtering, PCA method, Wavelet transform method, BM3D, TV-based regularization, NLM, R-NL, NCSR model, LRA_SVD, WNNM, DnCNN, and FFDNet. Among them, the first five are all filtering methods, while the last two are CNN-based methods. The remaining algorithms are variational denoising methods. In our experiments, the code and implementations provided by the original authors are used. All the source codes are run on an Intel Core i5–4570 CPU 3.20 GHz with 16 GB memory. The core part of the BM3D calculation is implemented with a compiled C++ mexfunction and is performed in parallel, while the other methods are all conducted using MATLAB[30]. Trials For a near report, the current denoising techniques embrace two variables (visual examination and execution measurements) to investigate the denoising execution. As of now, we can't track down any numerical or explicit techniques to assess the visual examination. All in all, there are three standards for visual investigation: (1) critical level of ancient rarities, (2) assurance of edges, and (3) reservation of surfaces. For picture denoising strategies, a few exhibition measurements are embraced to assess precision, e.g., PSNR and design closeness record estimation (SSIM). [In this examination, all picture denoising techniques work on uproarious pictures under three diverse clamor fluctuations σ ∈ [30, 50]. For the test pictures, we utilize two datasets for an intensive assessment: BSD68 and Set12. The BSD68 dataset comprises of 68 pictures from the different test set of the BSD dataset. The Set12 dataset, which is appeared in Fig. 1, is an assortment of generally utilized testing pictures. The extents of the initial seven pictures are 256 × 256, and the spans of the last five pictures are 512 × 512.

Comparison of filtering methods and variational denoising methods

We first present trial aftereffects of picture denoising on the 12 test pictures from the Set12 dataset. Figures 2 and 3 show the denoising correlation results by the sifting strategies variational denoising techniques, separately. From Fig.1, one can see that the spatial channels (Wiener sifting and Bilateral separating) denoise the picture better compared to the change space sifting techniques (PCA strategy and Wavelet change area technique). Notwithstanding, the spatial channels kill high recurrence clamor to the detriment of obscuring fine subtleties and sharp edges[31][32]. The aftereffect of collective separating (BM3D) has huge potential for commotion decrease and edge security. In Fig. 3, the visual evaluation shows that the denoising result of the TV-based regularization smooths the textures and generates artifacts. Although the R-NL and NLM methods can obtain better performances, these two methods have difficulty restoring tiny structures. Meanwhile, we find that the representative low-rank-based methods (WNNM, LRA_SVD and the sparse coding scheme NCSR produce better results in homogenous regions because the underlying clean patches share similar features, so they can be approximated by a low-rank or sparse coding problem.

Comparison of CNN-based denoising techniques

Here, we think about the denoising consequences of the CNN based strategies (DnCNN and FFDNet) with those of a few current compelling picture denoising techniques, including BM3D and WNNM. Supposedly, BM3D has been the most famous denoising technique over late years, and WNNM is a fruitful plan that has been proposed as of late. Table 1 reports the PSNR results on the BSD68 dataset. From Table 1, the accompanying perceptions can be made. In the first place, FFDNet beats BM3D by an enormous edge and outflanks WNNM by roughly 0.2 dB for a wide scope of clamor levels. Also, FFDNet is marginally substandard compared to DnCNN when the clamor level is low (e.g., $\sigma \leq 25$), yet it slowly beats DnCNN as the commotion level increments (e.g., $\sigma > 25$) [33][34]. In Fig. 4, we can see that the subtleties of the receiving wires and form regions are hard to recuperate. BM3D and WNNM obscure the fine surfaces, though the other two techniques reestablish more surfaces. This is on the grounds that Monarch has numerous tedious designs, which can be successfully misused by NSS [35][36]. Besides, the shape edges of these locales are a lot more honed and look more regular. Generally, FFDNet produces the best perceptual nature of denoised pictures.

Fig 1. Represents the test data from Set 12 [12]

(a) Weiner Filtering PSNR/SSIM (27.80/0.7071)

(b) Bilateral Filtering PSNR/SSIM (27.84/0.710)

(c) PCA Method PSNR/SSIM (26.56/0.591)

(d) Wavelet Filtering PSNR/SSIM (21.69/0.315)

(e) BM3D Filtering PSNR/SSIM (31.22/0.832)

Fig.2. Represent the Lena image for the visual comparison of different techniques with respect to parametric evaluation [37]

Fig. 3 Comparisons of denoising results on Boat image corrupted by additive white Gaussian noise with standard deviation [38-40], a. TV-based regularization (PSNR = 22.95 dB; SSIM = 0.456); b. NLM (PSNR = 24.63 dB; SSIM = 0.589); c. R-NL (PSNR = 25.42 dB; SSIM = 0.647); d. NCSR model (PSNR = 26.48 dB; SSIM = 0.689); e. LRA_SVD (PSNR = 26.65 dB; SSIM = 0.684); f. WNNM (PSNR = 26.97 dB; SSIM = 0.708

V. CONCLUSIONS

As the intricacy and necessities of picture denoising have expanded, research in this field is as yet popular. We have presented the new advancements of a few picture denoising techniques and examined their benefits and disadvantages in this paper. As of late, the ascent of NLM has supplanted the conventional nearby denoising model, which has made another hypothetical branch, prompting huge advances in picture denoising techniques, including inadequate portrayal, low-position, and CNN (all the more explicitly profound learning)- based denoising strategies. Albeit the picture sparsity and low-position priors have been broadly utilized as of late, CNN-based techniques, which have been end up being viable, have gone through fast development in this time. In spite of the numerous top to bottom investigations on eliminating AWGN, few have considered genuine picture denoising. The significant snag is the intricacy of genuine commotions on the grounds that AWGN is a lot less complex than genuine clamors. In the present circumstance, the careful assessment of a denoiser is a troublesome undertaking. There are a few segments (e.g., white equilibrium, shading demosaicing, commotion decrease, shading change, and pressure) contained in the in-camera pipeline. The yield picture quality is influenced by some outside and interior conditions, like brightening, CCD/CMOS sensors, and camera shaking. Albeit profound learning is growing quickly, it isn't really a viable method to take care of the denoising issue. The principle justification this is that genuine world denoising measures need picture sets for preparing. As far as we could possibly know, the current denoising strategies are totally prepared by mimicked boisterous information produced by adding AWGN to clean pictures. All things considered, for this present reality denoising measure, we track down that the CNNs prepared by such mimicked information are not adequately powerful. In rundown, this paper plans to offer an outline of the accessible denoising strategies. Since various kinds of commotion require diverse denoising techniques, the examination of clamor can be helpful in creating novel denoising plans. For future work, we should initially investigate how to manage different sorts of commotion, particularly those current, all things considered. Also, preparing profound models without utilizing picture sets is as yet an open issue. Plus, the procedure of picture denoising can likewise be extended to different applications.

References

[1] Yoshua Bengio, Patrice Simard, and Paolo Frasconi. Learning long-term dependencies with gradient descent is difficult. IEEE transactions on neural networks.

[2] Antoni Buades, Bartomeu Coll, and Jean-Michel Morel. Nonlocal image and movie denoising. International journal of computer vision, 76(2):123–139, 2008.

[3] Ying Tai, Jian Yang, Xiaoming Liu, and Chunyan Xu. Memnet: A persistent memory network for image restoration. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages.

[4] Chunwei Tian, Qi Zhang, Guanglu Sun, Zhichao Song, and Siyan Li. Fft consolidated sparse and collaborative representation for image classification. Arabian Journal for Science and Engineering.

[5] Subarna Tripathi, Zachary C Lipton, and Truong Q Nguyen. Correction by projection: Denoising images with generative adversarial networks. arXiv preprint.

[6] Lei Zhang and Wangmeng Zuo. Image restoration: From sparse and low-rank priors to deep priors. IEEE Signal Processing Magazine, 34(5):172–179, 2017.

[7] Yulun Zhang, Yapeng Tian, Yu Kong, Bineng Zhong, and Yun Fu. Residual dense network for image super-resolution. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018.

[8] Aharon M, Elad M, Bruckstein A (2006) rmK-SVD: an algorithm for designing overcomplete dictionaries for sparse representation. IEEE Trans Signal Process 54(11):4311–4322.

[9] Elad M, Aharon M (2006) Image denoising via sparse and redundant representations over learned dictionaries. IEEE Trans Image Process 15(12): 3736–3745.

[10] Zhang L, Zuo WM (2017) Image restoration: from sparse and low-rank priors to deep priors [lecture notes]. IEEE Signal Process Mag 34(5):172–179.

[11] Mairal J, Bach F, Ponce J, Sapiro G, Zisserman A (2009) Non-local sparse models for image restoration. In: Abstracts of the 12th international conference on computer vision. IEEE, Kyoto, pp 2272–2279.

[12] Zhang L, Dong WS, Zhang D, Shi GM (2010) Two-stage image denoising by principal component analysis with local pixel grouping. Pattern Recogn 43(4):1531–1549.

[13] Dong WS, Zhang L, Shi GM, Li X (2013) Nonlocally centralized sparse representation for image restoration. IEEE Trans Image Process 22(4):1620– 1630.

[14] Catté F, Lions PL, Morel JM, Coll T (1992) Image selective smoothing and edge detection by nonlinear diffusion. SIAM J Numer Anal 29(1):182–193.

[15] Esedoḡlu S, Osher SJ (2004) Decomposition of images by the anisotropic rudin-osher-fatemi model. Commun Pure Appl Math 57(12):1609–1626. https://doi.org/10.1002/cpa.20045

[16] Rudin LI, Osher S, Fatemi E (1992) Nonlinear total variation-based noise removal algorithms. In: Paper presented at the eleventh annual international conference of the center for nonlinear studies on experimental mathematics: computational issues in nonlinear science. Elsevier NorthHolland, Inc.

[17] Milanfar P (2013) A tour of modern image filtering: new insights and methods, both practical and theoretical. IEEE Signal Process Mag 30(1):106– 128.

[18] Donoho DL, Johnstone IM (1994) Ideal spatial adaptation by wavelet shrinkage. Biometrika 81(3):425 https://doi.org/10.1093/biomet/81.3.425 6. Shin DH, Park RH, Yang S, Jung JH (2005) Block-based noise estimation using adaptive gaussian filtering. IEEE Trans.

[19] Motwani MC, Gadiya MC, Motwani RC, Harris FC Jr (2004) Survey of image denoising techniques. In: Abstracts of GSPX. Santa Clara Convention Center, Santa Clara, pp 27–30

[20] Jain P, Tyagi V (2016) A survey of edge-preserving image denoising methods. Inf Syst Front 18(1):159–170.

[21] Diwakar M, Kumar M (2018) A review on CT image noise and its denoising. Biomed Signal P.

[22] . Coupe P, Yger P, Prima S, Hellier P, Kervrann C, Barillot C (2008) An optimized blockwise nonlocal means denoising filter for 3-d magnetic resonance images. IEEE Trans Med Imaging 27(4):425–441.

[23] Thaipanich T, Oh BT, Wu PH, Xu DR, Kuo CCJ (2010) Improved image denoising with adaptive nonlocal means (ANL-means) algorithm. IEEE Trans Consum Electron 56(4):2623–2630.

[24] Wang J, Guo YW, Ying YT, Liu YL, Peng QS (2006) Fast non-local algorithm for image denoising. In: Abstracts of 2006 international conference on image processing. IEEE, Atlanta, pp 1429–1432.

[25] Goossens B, Luong H, Pizuirca A (2008) An improved non-local denoising algorithm. In: Abstracts of international workshop local and non-local approximation in image processing. TICSP, Lausanne, p 143

[26] Pang C, Au OC, Dai JJ, Yang W, Zou F (2009) A fast NL-means method in image denoising based on the similarity of spatially sampled pixels. In: Abstracts of 2009 IEEE international workshop on multimedia signal processing. IEEE, Rio De Janeiro, pp 1–4

[27] Tschumperlé D, Brun L (2009) Non-local image smoothing by applying anisotropic diffusion PDE's in the space of patches. In: Abstracts of the 16th IEEE international conference on image processing. IEEE, Cairo, pp 2957– 2960.

[28] Zhang K, Zuo WM, Chen YJ, Meng DY, Zhang L (2017) Beyond a Gaussian denoiser: residual learning of deep CNN for image denoising. IEEE Trans Image Process 26(7):3142–3155.

[29] Zhang K, Zuo WM, Zhang L (2018) FFDNet: toward a fast and flexible solution for CNN-based image denoising. IEEE Trans Image Process 27(9): 4608–4622. https://doi.org/10.1109/TIP.2018.2839891 108. Cruz C, Foi A, Katkovnik V, Egiazarian K (2018) Nonlocality-reinforced convolutional neural networks for image denoising. IEEE Signal Process Lett 25(8):1216–1220.

[30] Wang Z, Bovik AC, Sheikh HR, Simoncelli EP (2004) Image quality assessment: from error visibility to structural similarity. IEEE Trans Image Process 13(4):600–612.

[31] Roth S, Black MJ (2005) Fields of experts: A framework for learning image prior. In: Paper presented at the IEEE computer society conference on computer vision and pattern recognition, IEEE Computer Society, Washington, 20–26 June, 2005.

[32] Liu SG, Wang XJ, Peng QS (2011) Multi-toning image adjustment. Comput Aided Draft Des Manuf 21(2):62–72

[33] Yu WW, He F, Xi P (2009) A method of digitally reconstructed radiographs based on medical CT images. Comput Aided Draft Des Manuf.

[34] Bertalmío M (2018) Denoising of photographic images and video: fundamentals, open challenges and new trends. Springer Publishing Company, Berlin.

[35] Guo Q, Zhang CM, Zhang YF, Liu H (2016) An efficient SVD-based method for image denoising. IEEE Trans Circuits Syst Video Technol 26:868–880.

[36] Liu GC, Lin ZC, Yan SC, Sun J, Yu Y, Ma Y (2013) Robust recovery of subspace structures by low-rank representation. IEEE Trans Pattern Anal Mach Intell 35(1):171–184.

[37] Candès EJ, Shen ZW (2010) A singular value thresholding algorithm for matrix completion. SIAM J Optim 20(4):1956–1982. https://doi.org/10. 1137/080738970 81. Hou JH (2007) Research on image denoising approach based on wavelet and its statistical characteristics. Dissertation, Huazhong University of Science and Technology.

[38] Jiao LC, Hou B, Wang S, Liu F (2008) Image multiscale geometric analysis: theory and applications. Xidian University press, Xi'an 83. Zhang L, Bao P, Wu XL (2005) Multiscale lmmse-based image denoising with optimal wavelet selection. IEEE Trans Circuits Syst Video Technol 15(4): 469–481.

[39] Jain P, Tyagi V (2013) Spatial and frequency domain filters for restoration of noisy images. IETE J Educ 54(2):108–116.

[40] Jung A (2001) An introduction to a new data analysis tool: independent component analysis. In: Proceedings of workshop GK. IEEE, “nonlinearity”, Regensburg, pp 127–132 86. Hyvarinen A, Oja E, Hoyer P, Hurri J (1998) Image feature extraction by sparse coding and independent component analysis. In: Abstracts of the 14th international conference on pattern recognition. IEEE.