An effective nonlocal means image denoising framework based on non-subsampled shearlet transform

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Abstract
Image denoising is a fundamental task in computer vision and image processing system with an aim of estimating the original image by eliminating the noise and artefact from the noise-corrupted version of the image. In this study, a nonlocal means (NLM) algorithm with NSST (non-subsampled shearlet transform) has been designed to surface a computationally simple image denoising algorithm. Initially, NSST is employed to decompose source image into coarser and finer layers. The number of decomposition levels of NSST is set to two, resulting in set of low-frequency coefficients (coarser layer) and four sets high-frequency coefficients (finer layers). The two number of levels of decomposition are used in order to preserve memory, reduce processing time, and mitigate the influence of noise and misregistration errors. The finer layers are then processed using NLM algorithm, while the coarser layer is left as it is. The NL-Means algorithm reduces noise in finer layers while maintaining the sharpness of strong edges, such as the image silhouette. When compared to noisy images, this filter preserves textured regions, resulting in retaining more information. To obtain a final denoised image, inverse NSST is performed to the coarser layer and the NL-means filtered finer layers. The robustness of our method has been tested on the different multisensor and medical image dataset with diverse levels of noise. In the context of both subjective assessment and objective measurement, our method outperforms numerous other existing denoising algorithms notably in terms of retaining fine image structures. It is also clearly exhibited that the proposed method is computationally more effective as compared to other prevailing algorithms.

Keywords Nonlocal means · Image denoising · Multiscale decomposition · Nonsubsampled Laplacian pyramid (NSLP) · Shearlet filter

1 Introduction
Image denoising is the process to eliminate noise or distortions from the images. It is mostly used as image pre- or post-processing to boost the quality of the processed images for further image analysis and understanding. Digital image is often prone to noise degradation during the image acquisition in imaging systems owing to sensor characteristics and complex camera processing procedures (Nam et al. 2016; Mildenhall et al. 2018). The elimination of noise from the captured image is a necessary step for improving image quality in computer vision applications (Foi et al. 2008; Liang et al. 2018). Denoising of images in general seeks to obtain a clear image \( x \) from a noisy observation \( y = x + n \), in which \( n \) is the corrupted noise. An AWGN (additive white Gaussian noise) having standard deviation (\( \sigma \)) is a popularly used assumption on \( n \). In particular, removal of noise that is varying at different settings and follows normal distribution (Xu et al. 2018), has got a lot of attention lately. Image priors are of key importance for image denoising from the Bayesian perspective (Lefkimmiatis 2018). In the past few decades, several techniques have been proposed to exploit the image priors for image denoising (Elad and Aharon 2006;
These algorithms are roughly categorised into nonlocal self-similarity (NSS)-related algorithms (Buades et al. 2005a), low rankness or sparsity-related methods (Mao et al. 2016), dictionary learning-related methods (Dong et al. 2012), generative learning-related algorithms (Pajot et al. 2018), and discriminative learning-related algorithms (Mao et al. 2016) are few examples. The NSS prior is derived from the fact that a local patch in the natural image has several nonlocal similar patches across the images where, Euclidean distance is often used to measure the similarity. Existing denoising algorithms have successfully utilized the NSS prior, for example, BM3D (Dabov et al. 2007a), WNNM (Gu et al. 2017), and N3Net (Plötz and Roth 2010), among others. Regardless their ability to improve denoising quality, this patch level NSS prior utilized in this method undergoes one major obstacle, i.e. they tend to introduce artefacts around the edges. This can be attributed to the fact that finding nearly identical patches for complete reference patches in the natural image is quite difficult, particularly when the number of identical patches is more. BM3D-SAPCA (Dabov et al. 2009) proposed a solution to overcome this flaw of finding shape adaptive similar patches. Further another improvement can be observed in Hou et al. (2010). However, shape artefacts would be included in the denoised images as a result. Multiscale strategies (Zontak et al. 2013) have been introduced for improving the similarity; however, the information would be lost in the course level and same counterparts would be failed to detect. In this work, we take the advantage of both spatial and transform domain denoising by integrating the nonlocal means algorithm and NSST. The key concept of our work is demonstrated in Fig. 1. With the help of multiscale directional transform, i.e. the geometry of multidimensional data can be captured using the NSST. Shear parameters are then used to capture the singularities. The nonlocal mean filtering facilitates preservation of edge features and details of the multi-resolution representation. High-contrast elements such as textures in general are rarely preserved while suppressing noise. As a result, this serves as a motivation to use a combination of non-subsampled shearlet transform and a nonlocal means algorithm to denoise images. The advantages of combined adaptable approach especially exhibit the capacity to extract multidimensional data geometry. It could also effectively indicate edges in high noise images. The remainder of this paper is organised as follows: Sect. 2 broadly summarises the previous related works. Section 3 illustrated a key concept of NSST. The proposed image denoising method using NSST decomposition and the nonlocal means algorithm is demonstrated in Sect. 4. Section 5 is dedicated to exhibit the numerous experimental results which demonstrates the analysis, discussions, and efficiency of our method with other comparative methods. Finally, a summary of the conclusion is mentioned in Sect. 6.

2 Summary of previous works

In this section, recent developments of image denoising are presented and discussed. Self-similar patches are used in many important denoising algorithms; NLM (NonLocal Means Algorithm) (Buades et al. 2005b) and BM3D (Block Matching 3D transform) (Dabov et al. 2007b). Many versions have been proposed as a result of their improvisation and evolution, including SADCT (Shape Adaptive Discrete Cosine Transform) (Foi et al. 2007), SAPCA (Shape Adaptive Principal Component Analysis) (Dabov et al. 2009) and many more that explore self-similar patches in transform domain. The dictionary learning-oriented algorithms (Elad and Datsenko 2009) use self-identical patches and learn overcomplete dictionaries from clear image to recognise and formulate sparsity. Numerous algorithms (Zoran and Weiss 2011; Chen et al. 2015) have looked for using the maximum likelihood approach to train the statistical priors, such as the Gaussian mixture model (GMM) of natural patches or patch reconstruction. For multi-resolution study on transform domain methods, a novel multiscale directional transform known as shearlet has been proposed in the literature. The single shearlet function (Guo and Labate 2007) is defined by the direction of the singularities, a translation and a shear. However, it has unbound support depending on the space domain, as well as functions that are band-limited. As a result, the spatial domain efficiently helps the compact representation components for local characteristics of any images. (Easley et al. 2008a). NSST can also accurately characterise an image’s geometric and textural features (Yang et al. 2014). It has the ability to breakdown an image into the number of directional elements. A NSST has a lower computing complexity and sparse approximation capabilities than the NSCT (nonsubsampled contourlet transform) (Guorong et al. 2013). By introducing the texture measure as smooth penalty weight or spatially varying data fidelity in the sparse norm and non-local total variation algorithms, the nonlocal version of generalised RTV (NLGRTV) for denoising has been introduced in Liu et al. (2014). The important concept is to employ the updated texture measure as the spatially changing penalty weight and substitute local candidate pixel in the smooth-penalty term with the nonlocal set (Liu et al. 2014). Takeda et al. (2008) extend the application of kernel regression to deblurring. This algorithm employed a novel image prior that generalises some of the most widely used regularisation techniques. Chambolle et al. (2010) addressed a wide range of...
theoretical and practical aspects of total variation-based image reconstruction algorithms. Graham Treece has suggested a rather recent filter based on morphological filtering for adaptively eliminating the quantity of noise contained in the images. It is called bitonic filtering and works on the idea of bitonicity which means it keeps image information that is locally bitonic, i.e. a signal comprising of one minima or maxima in the given range. It targets to remove the noise pixels that are constantly varying with low range of frequency. The bitonic filtering is the nonlocal filter that creates a weighted Gaussian result by combining the opening and closing weights of filter. It is a type of adaptive image denoising that keeps edges whilst reducing noise without requiring advance knowledges of the quantity of noise. In case of AWGN and impulse noise, this filter has superior denoising efficiency than median, Gaussian, etc., filters (Treece 2016). B.K Shreyamsha presented a noise thresholding and Gaussian/Bilateral filtering-based denoising method. An idea of method noise has been proposed in this scheme. The dissimilarity between the input image and denoised image using a particular approach is referred to as method noise. The noisy images are supposed to be contaminated/degraded via Gaussian additive noise having zero mean and a known variance has been regulated to test at low and high noise value in GBFMT (Kumar 2013a). The contaminated images are filtered utilizing bilateral filtering and the resulting residual images are hard thresholded in the wavelet domain. In a similar study, a nonlocal filter was used instead of a bilateral filter to take use of the idea of method noise thresholding (NLMNT) (Kumar 2013b). A method known as WBF (weighted bilateral filter) has been developed optimising standard bilateral filtering and its adaptation in the weighted form with the goal of minimising the MSE (mean square error). Chaudary et al. presented the sure and fast strategy for image denoising by utilising bilateral filter (Chaudhury and Rithwik 2015). Random field methods are another popular topic that is often used in image denoising along with other low-level processing applications including image segmentation and classification. In this algorithm, the intensity of a pixel is determined by its neighbours. These algorithms are primarily based on the principle that the global representation of images may be generated through its local physical structure that is done using the conditional probability distribution function known as Markov random field (MRF) (Rangarajan and Chellappa 1995). Tomasi and Munich proposed the bilateral filter (BF) as the improvised version of neighbouring filter that weighs the distance to the reference pixels rather than following the fixed neighbourhood (Tomasi and Manduchi 1998). The authors of the paper (Goyal et al. 2020) have summarised the comparison classification and assessment of several image denoising algorithms. A large number of researchers have put in a lot of time and efforts

![Image of the proposed method framework](https://example.com/image.png)
to create a structural literature that shows significant progressive growth achieved through the series of sequential incremental enhancements. Goyal et al. (2018a) proposed an effectual denoising method based on NSST domain morphological filtering and Bitonic filtering. With the use of morphological techniques, structural information and contrast has been regulated. NSST accurately represents the detailed directional features (Goyal et al. 2018b). In multi-baseline InSAR (interferometric synthetic aperture radar), interferometric phase filtering is a critical step. Multi-baseline interferometric phase filtering methods primarily follow single baseline INSAR approaches and which do not fully exploit its data supremacy is being proposed in Liu et al. (2020), i.e. statistically based joint filtering of multi-baseline InSAR. An innovative framework for denoising of images based on NSST and bilateral filtering is discussed in Routray et al. (2020). This method employs NSST to separate high and low-frequency coefficients of a noisy input image. The noise from the low-frequency coefficient is removed using the weighted bilateral filter (WBF), while noise from the high-frequency coefficient is removed using thresholding (Routray et al. 2020). The continued advancement and widespread uses of CT (computed tomography) in medical imaging have increased the exposure of high radiation doses to the patients. However, using low radiation dose might result in increased noise and artefacts that adversely affects radiodiagnosis. This issue has been addressed in the nonsampled shearlet (NSST) domain in Diwakar and Singh (2020). It is a strategy based on a novel shrinkage function. The proposed approach uses SURE-LET (stein unbiased risk of estimation & liner expansion of threshold) technique for effectively modelling noise on multivariate shrinkage algorithms. The enhanced nonlocal means (NLM) along with NSST been used to develop a new denoising methodology for MRI images (Sharma and Chaurasia 2021). The parameters have been tuned to maximise output while maintaining high-quality denoising. The image restoration algorithms have largely focussed on removal of AWGN as it degrades the uniform information subsequent and hinders subsequent image processing at large. A new framework for multi-level image denoising is proposed in Chakraborty et al. (2021) which progressively reduces Gaussian noise while retaining information as much as possible. The advantages of complex-valued process such as the closeness of the convolution provided by the tensor products of 1D complex-valued filters, noise stability of residual blocks and nonlinear activation on are exploited by introducing a CNN for denoising of images with key computational operation described in the complex number field in Quan et al. (2021). A novel model-based denoising approach has been proposed by incorporating the nonlinear filtering operator, a reliability matrix, and a high-dimensional feature transformation function into the traditional consistency prior to simultaneously incorporate the valuable achievements of traditional methods into the network design while also improving network interpretability (Ren et al. 2021).

Fig. 2 Two level multiscale and multidirectional decomposition of NSST
Fig. 3 Input images a House; b MRI; c PAN

Fig. 4 A source MRI image contaminated by Gaussian noise on $\sigma$ (standard deviation) = 10, 20, 30, 40, 50

Fig. 5 A source House image contaminated by Gaussian noise on $\sigma$ (standard deviation) = 10, 20, 30, 40, 50

Fig. 6 A source PAN image contaminated by Gaussian noise on $\sigma$ (standard deviation) = 10, 20, 30, 40, 50
3 Nonsubsampled shearlet transform [NSST]

Shearlet is considered as an extremely appropriate sparse directional image representation frame within MST (Multiscale transform) theory so far (Du et al. 2016). These are affine systems with composite dilation of dimension $n = 2$ and are explained as follows.

$$
W_{j,l,k}(x) = |\text{det}A|^{1/2} \Psi \left( s^t A^t x - k \right),
$$

(1)

where $\Psi \in L^2(\mathbb{R})^2$. $A$ is an anisotropic matrix that is related to scale transformation, and $S$ is the shear matrix that is affiliated via area-preserving geometrical transformation, for example, rotations and shear.

The scale, direction and shift parameter are denoted $j, l$ & $k$, respectively. For each $a > 0$ & $s \in \mathbb{R}$, the matrices $A$ and $S$ play the crucial role in the ST operation and represented as follows (Easley et al. 2008b)

$$
A = \begin{bmatrix} a & 0 \\ 0 & \sqrt{a} \end{bmatrix}, \quad S = \begin{bmatrix} 1 & s \\ 0 & 1 \end{bmatrix}
$$

(2)

If we assume that $a = 4$ and $s = 1$; we get

$$
A = \begin{bmatrix} 4 & 0 \\ 0 & 2 \end{bmatrix}, \quad S = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}
$$

Let $A_1 = \begin{bmatrix} 4 & 0 \\ 0 & 2 \end{bmatrix}$ and $S_1 = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$, for any $\xi = (\xi_1, \xi_2) \in \mathbb{R}^2$ and $\xi_1 \neq 0$; also let $\Psi^{(0)}$ and $\Psi^{(1)}$ is specified by

$$
\hat{\Psi}^{(0)}(\xi) = \hat{\Psi}^{(0)}(\xi_1, \xi_2) = \hat{\Psi}_1(\xi_1) \hat{\Psi}_2 \left( \frac{\xi_2}{\xi_1} \right)
$$

(3)

$$
\hat{\Psi}^{(1)}(\xi) = \hat{\Psi}^{(1)}(\xi_1, \xi_2) = \hat{\Psi}_1(\xi_1) \hat{\Psi}_2 \left( \frac{\xi_1}{\xi_2} \right)
$$

(4)

where $\hat{\Psi}_1, \hat{\Psi}_2 \in C^\infty(\mathbb{R})$, supp $\hat{\Psi}_1 \subset [-\frac{1}{2}, -\frac{1}{16}] \cup [\frac{1}{16}, 1/2]$, and supp $\hat{\Psi}_1 \subset [-1, 1]$.

Each element of $\hat{\Psi}_{j,l,k}$ is supported by the pair of trapezoids, approximately $2^j \times 2^j$ in size, orientated along slope lines $l = 2^{-j}$.

The ST function is then obtained:

$$
\Psi^{(0)}_{j,l,k}(x) = 2^j \Psi^{(0)} \left( s^t A^t_{j,l} x - k \right)
$$

$$
\Psi^{(1)}_{j,l,k}(x) = 2^j \Psi^{(1)} \left( s^t A^t_{j,l} x - k \right)
$$

(5)
where \( j \geq 0, -2^j \leq l \leq 2^j - 1 \), and \( k \in \mathbb{Z}^2 \).

ST has the following characteristics: good spatial and frequency localisation, robust anisotropic directionality selectivity, good parabolic scaling and sparse representation. Still, ST causes a Gibbs phenomenon due to the shortage of shift invariance. The version of shift invariant form of ST is NSST. A NSLP (nonsampled Laplacian pyramid) filters are utilised as a replacement for LP filters utilised in the ST operation. NSLP implements multiscale decomposition. Each NSLP decomposition level can generate one low-frequency and one high-frequency coefficient. Then, repeatedly, the next NSLP decomposition is conducted on the last (prior) low-frequency coefficient in order to capture the singularities of an input image. When the decomposition level is set at \( J \), input image is decomposed into \( J + 1 \) coefficients of equal size of the input image, one of that is the low-frequency coefficient. To achieve multidirectional factorization, a shear filter (SF) is applied to the high-frequency coefficients of each NSLP decomposition level without sub-sampling ensuring the shift invariance quality of NSST. Suppose, perform/stages of directional decomposition on the high-frequency coefficient decomposes by NSLP, resulting in \( 2^l \) directional sub-bands of similar size as input (Easley et al. 2008b). Figure 2 depicts the two-level decomposition of the NSST. NSLP decomposition and their corresponding directional decomposition by SF are depicted in the schematic diagram in Fig. 2.
4 Proposed denoising method

This section presents a proposed denoising technique that combines NSST decomposition, NL-Means algorithm, and inverse NSST. The proposed denoising approach consists of three stages: NSST decomposition, NL-Means filtering of finer layers and NSST reconstruction. Figure 1 depicts the illustrative framework of proposed method. First, a NSST decomposition yields low and high-frequency coefficients that reflect various feature information. The coarser elements of the input image contain low-frequency coefficient, while the finer detailed features contain the high-frequency coefficients. The more visual significant details and contrast information can be found in the coarser layer of the images. More contour and edge information are provided by the finer layers of images. The finer layers are then processed using a nonlocal means algorithm, while the coarser layer is left as it is. It is possible to retain feature, i.e. edges and structures of finer detailed layers using the nonlocal means algorithm. Finally, using inverse NSST to the base layer and the NLM filtered detail layers, a denoised image is obtained.

4.1 NSST implementation steps

The NSST could be achieved in two steps.

4.2 Multiscale decomposition

To achieve multi-resolution decomposition, a NSP (nonsubsampled pyramid) filter bank decomposes each input image in the set of low and high-frequency sub-images. Firstly, NSP decomposes input image into low-frequency and high-frequency coefficient. The singular points will be generated by iterating the NSP decomposition of each layer on the low-frequency coefficients retrieved by upper layer decomposition. The sub-band image will possess same size as input image if down-sampling is not performed. Finally,
we get a low pass image and the $j$ band pass images from $j$ level decomposition.

**4.3 Directional localization**

To achieve multi-direction decomposition, the shearlet filter bank decomposed this high-frequency sub-images. The pseudo-polarisation coordinates are first converted to Cartesian coordinates. A “Meyer” wavelet is then utilised to create a window function and create shearlet filters. Lastly, the directional sub-band images are obtained by convolving the sub-band images with “Meyer” window function. Figure 2 indicates the two-level decomposition representation. The source image $A$ is decomposed by NSST in low-frequency bands; $L_A(m,n)$ as well as high-frequency coefficient $H^A_{k,l}(m,n)$. The decomposed high-frequency coefficient in the $k^{th}$ direction the $l^{th}$ decomposition level is denoted by $k$ and $l$. The domain variables of the NSST are indicated by letters $m$ and $n$. One low-frequency coefficient and four high-frequency coefficients of input image are achieved by the two-level NSST decomposition.

**4.4 The Nonlocal means algorithm**

A nonlocal means algorithm (Rousselle et al. 2012) is the nonlinear, edge preserving filter which calculates each output pixels as the weighted sum of the input pixels. The set of input pixels which contribute to one output pixel will come from the large region of source image; hence, it is called a nonlocal. The weights are computed by distance between small image patches which is the key property of
nonlocal means filter. A nonlocal means filter is the variant of bilateral filter (Tomasi and Manduchi 1998) that computes filter weights based on distance between pair of pixel values rather than small patches. Denoising performance is greatly enhanced as a result of this extension, and nonlocal means and its versions are among the mostly used denoising techniques.

The nonlocal means filter calculates the filtered value $\hat{u}(p)$ of a pixel $p$ in a colour image $u = (u_1, u_2, u_3)$ as the weighted average of pixel in the square neighbourhood of size $2r+1 \times 2r+1$ centred on $p$, as defined by

$$\hat{u}_i(p) = \frac{1}{C_P} \sum_{q \in N(p)} u_i(q) w(p, q)$$

(6)

where $N(p)$ is the square neighbourhood centred on $p$, $w(p, q)$ represent weight contribution of $q$ to $p$, $i$ represents colour channel index, and $C(p)$ represents normalisation factor,

$$C(p) = \sum_{q \in N(p)} w(p, q)$$

(7)

A distance between the pair of small patches of size $2f+1 \times 2f+1$ centred at $p$ & $q$ is used to calculate the weight $w(p, q)$ of a neighbour $q$. The average of per-pixel and per-colour channel squared distance $d^2_i(p, q)$ over the patches is called the patch distance $d^2(P(p), P(q))$. 

Fig. 11 MRI image at $\sigma = 50$, denoising result a NLGRTV, b Ker. Reg., c TV1, d Bitonic, e NLFMT, f GBFMT, g RBF, h MRF, i SBF, j Proposed
Here, $P(0)$ indicates the offset to each pixel within a patch, and $P(p)$ & $P(q)$ are the patches centred on $p$ and $q$, respectively. The computed squared distance is biased due to the noisy input image, which is an important observation. As a result, the original nonlocal means filter subtracts the variance of the computed squared distance from the patch distance to remove the noise contributions. A modified patch distance is calculated using uniform pixel noise with variance $\sigma^2$ & uncorrelated pixels $p$ & $q$ as:

$$\max(0, d^2(P(p), P(q)) - 2\sigma^2)$$

An exponential kernel is then used to calculate the weight $w(p, q)$ of the contribution of pixel $q$ to $p$ as:

$$w(p, q) = \exp\left(\frac{\max(0, d^2(P(p), P(q)) - 2\sigma^2)}{2\sigma^2} \right)$$

where $k$ is a damping factor set by the user to control the strength of filter. A more conservative filter is produced with a lower $k$ value.

We also employ the patchwise extension described by Buades et al. 2005c, which results in outputs that are slightly smoother. We weight complete pixels in the patch centred at $p$ with $w(p, q)$ in place of weighting only the pixel $p$ at the centre of patch with the weight $w(p, q)$. Each pair of pixels appears as $2f + 1 \times 2f + 1$ patches. Every time with the different weight $w(p + n, q + n)$, where $n$ is the offset of $p$ and $q$ in the patch. A final weight $W(p, q)$ for the pair of pixels in the patchwise implementation is just the
average of complete weights which involve these two pixels;
\[
W(p, q) = \frac{1}{(2f + 1)^2} \sum_{n \in P(0)} w(p + n, q + n) 
\]  \hspace{1cm} (12)

The value of \( \sigma \) determines the size of the patch and research window. When \( \sigma \) increases, we need a larger patch to ensure that patch comparison is reliable. At the same time, we need to enhance the research window to boost the algorithm’s noise removal capabilities by locating more similar pixels. Where \( h = k\sigma \) is the value of the filtering parameter. As the dimension of the patch increases, the value of \( \sigma \) drops. The distance between two pure noise patches concentrates more around \( 2\sigma^2 \) for larger sizes, and hence, a smaller value of \( k \) can be utilised for filtering.

4.5 NSST reconstruction

In order to generate a final denoised image, inverse NSST is applied to base layer and the NLM filtered detail layers.

4.6 Performance metrics

The method of evaluation is required to demonstrate the effectiveness of the denoising methods. Subjective and objective assessment methods are two types of evaluation procedures that are often used. Qualitative approaches are manmade visual analysis that aids in describing the visual quality of the images. There are variety of strategies that can be employed for objective analysis (Goyal et al. 2018a). The PSNR and its mean value are quantitative evaluation metrics estimated for measuring the effectiveness of denoised image reconstructed in our method. The
PSNR is expressed in decibels. The larger the PSNR value, the greater the quality of the resulting denoised image. It is computed as follows:

$$PSNR = 10 \log_{10} \left( \frac{MAX^2_i}{MSE} \right)$$

(13)

where $MAX_i$ indicates the maximum possible pixel value of an image. The cumulative error between an original image and denoised image is called mean squared error (MSE). The lower the estimated MSE value, the superior the image denoising performance. It is computed as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

(14)

The vector $n$ predictions are derived from the sample on $n$ data points on all variables and $Y$ is the vector of observed values of the variable being predicted, with $\hat{Y}$ being the predicted values.

To further assess the consistency of the different algorithms, we introduce calculating the mean/average of PSNR values, which may be computed as follows,

$$\text{Mean} = \frac{\sum_{i=0}^{n} PSNR_i}{n}$$

(15)

Above metric can be used to determine the stability in the performance of the different algorithms at various noise levels.

Fig. 14 House image at $\sigma = 30$, denoising result

(a) NLGRTV, (b) Ker. Reg., (c) TV1, (d) Bitonic, (e) NLFMT, (f) GBFMT, (g) RBF, (h) MRF, (i) SBF, (j) Our method.
5 Experimental setup, results and discussion

5.1 Experimental setup

With the aim to test the effectiveness of our denoising method, we have utilized three images: house image, magnetic resonance imaging (MRI) image and panchromatic (PAN) image that is remote sensing, medical and natural image, respectively (https://www.mathworks.com, matlabcentral, fileexchange, 67703-image-processing-dataset-for-color-grey-image-fusion--image-blending--image-denoising--enhancement [Accessed on 2016, 15, pp. 06. 2016]). We had evaluated the effectiveness of our denoising method with different sets of images. The images are of size 256*256 pixels. The efficiency of our method was evaluated utilizing standard 8-bit grayscale image contaminated by zero mean white Gaussian noise. The proposed method has been performed in MATLAB 2019b on Intel (R) core (TM) i3-7020 CPU @ 2.70 GHz system with 8 GB memory. An effectiveness of our method is compared with NLGRTV (Liu et al. 2014), Locally Adaptive Kernel Regression (LARK) (Takeda et al. 2008), Total variation minimization (Chambolle et al. 2010), Bitonic filter (Treece 2016), GBFMT (Kumar 2013a), NLFMT (Kumar 2013b), RBF (Chaudhury and Rithwik 2015), Markov Random Field (MRF) (Rangarajan and Chellappa 1995) and SBF (Tomasi and Manduchi 1998). For this experiment, a radius of the Gaussian filter is set to 3 (three); however, as larger value could induce excessive smoothing and blurring. For SBF, the spatial kernel parameter is set to 4 (four), and a kernel range parameter is set at 20. The performance of our method is measured for $\sigma$.
= 10, 20, 30, 40 and 50 for low to high noise levels. The standard test images are shown in Fig. 3. These images are then added with white Gaussian noise of difference variance. The noisy image for MRI, House, and PAN is shown in Figs. 4, 5, and 6 at various levels of noise.

5.2 Experimental results

This section demonstrates an experimental results achieved by processing the standard test image datasets used in our algorithm and results are compared visually as well as quantitatively with several algorithms such as NLGRTV (nonlocal version of general relative total variation), Locally Adaptive Kernel Regression (LARK), Total variation minimization, Bitonic filter, NLFMT, GBFMT, RBF, Markov Random Fields (MRF), SBF and proposed method. The results are provided for all three datasets and five distinct noise give the comparative visual analysis and quantitative results at various settings. The qualitative evaluation results for the MRI at \( \sigma = 10 \) are shown in Fig. 7a–j. Figures 8, 9, 10 and 11 demonstrate the findings of MRI using various algorithms with noise levels of \( \sigma = 10, 20, 30, 40 \) and 50. The visual findings for the house image at \( \sigma = 10, 20, 30, 40 \) and 50 utilizing various approaches are shown in Figs. 12, 13, 14, 15 and 16. Similarly, Figs. 17, 18, 19, 20 and 21 demonstrate the denoised performance of PAN image at \( \sigma = 10, 20, 30, 40 \) and 50, respectively, using various algorithms. Table 1 demonstrates the objective performance with regard to PSNR values at \( \sigma = 10, 20, 30, 40 \) and 50 utilizing the

![Fig. 16 House image at \( \sigma = 50 \), denoising result a NLGRTV, b Ker. Reg., c TV1, d Bitonic, e NLFMT, f GBFMT, g RBF, h MRF, i SBF, j Our method](image-url)
5.3 Result analysis and discussion

We have demonstrated the qualitative and quantitative evaluations of our proposed algorithm in this section and compared it with other algorithms.

5.3.1 Qualitative evaluation

We have evaluated the proposed denoising algorithm with PSNR value, mean value and visual human perception after implementing it. In order to evaluate our findings, we considered three images: MRI, House, and PAN. Despite the fact that PSNR measures the intensity differences between the images, qualitative analysis plays the prominent role in order to verify and validate the visual quality of the denoised image of image quality is crucial for qualitative judgement. It aids in identifying whether or not edge features are retained, to examine either images carry artefacts and either noise has been eliminated. From Figs. 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19 and 21, it is noticeable that our method surpasses other prevailing methods in the context of qualitative analysis at standard deviations of $\sigma = 10, 20$ and $30$. Therefore, at low to moderate levels such as at standard deviation $\sigma = 10, 20$ and $30$, our method retained edges and sharp gradients, also tips are crisper, boundaries and counters are well sharp after removing noise. Therefore, practically at low to moderate noise levels, our method performs better than prevailing methods. As a result, proposed method has performed better visual performance than other benchmarking methodologies such as NLGRTV, LARK, Total variation minimization, Bitonic filter, NLFMT, GBFMT, RBF, Markov Random Fields (MRF), SBF and proposed method and our proposed algorithm for MRI image, PAN image & House image.

![Fig. 17 PAN image at $\sigma = 10$, denoising result](image)
variation minimization, Bitonic filter, NLFMT, GBFMT, RBF, Markov Random Fields (MRF), SBF. However, NLFMT, GBFMT, MRF, and SBF have performed quite similar visual performance at low to moderate noise levels as compared to proposed method but rest of the approaches failed miserably in maintaining fine textures and causes over-blurring of the images, resulting in data loss. A proposed method produces overall better visual results when compared to other algorithms and simultaneously emerges as a preferable algorithm for quality performance at low to moderate noise levels. Our method performs nearly better performance as compares to other benchmarking methods. Despite the fact that the algorithm was created to deal with noise at moderate and high noise levels, but our method is efficient to obtain comparable results at low noise levels too. The following factors are responsible for the improving the performance of proposed method, i.e. nonsubsampled shearlet transform (NSST) has potential to capture the geometry of multidimensional information. Shear parameters are then used to capture the singularities. The non-local means filter reduces noise in detail images while maintaining the sharpness of strong edges, such as the image silhouette. When compared to noisy images, this filter also smooths textured regions, resulting in more information. The combined technique can able to combine the benefits of efficient algorithms having exceptional ability to extract multidimensional data geometry. It could also effectively present edges in low noise for any given image. Bitonic filter and RBF perform roughly identical and somewhat better in terms of visual perception, but with insufficient noise removal and loss of fundamental feature information. Bitonic outperforms Ker, Reg, TV1, and NLGRTV algorithms because it removes high amount of noise from the images. The proposed approach, on the other hand, was able to totally eradicate the noisy pixels and maintain sharp edges and smooth gradients. We

Fig. 18 PAN image at $\sigma = 20$, denoising result a NLGRTV, b Ker. Reg., c TV1, d Bitonic, e NLFMT, f GBFMT, g RBF, h MRF, i SBF, j Our method
zoomed in on different regions of an image to check the fine texture details of denoised image and noticed that the texture details are more clearly visible in the images in proposed algorithm, however, while zooming images in other methods result in the presence of noise pixels instead of texture details. As a result, the proposed method may be concluded that it maintains better performance than other comparative algorithms in case of qualitative assessment.

5.3.2 Quantitative evaluation

In order to assess the effectiveness of our method quantitatively, we have computed PSNR value and its mean value for the test image datasets. The quantitative assessment of our method along with other methods is illustrated in Table 1. As shown in Table 1, the objective metric values of our algorithm are generally greater than other comparative algorithms. The PSNR values clearly show that proposed algorithm performs better at moderate to high noise levels from Table 1. Whereas the results of proposed algorithm are slightly better at low noise level, meanwhile still appropriate and effective as compares to other existing algorithms. Given that the noise levels of the image to be denoised are undefined beforehand, therefore selecting a good denoising filter only due to PSNR performance is not reasonable. In order to overcome this problem, we propose to measure the mean value of PSNR, which exhibits the stability in the performance of different algorithms across various range of noise levels. Table 1 shows that proposed algorithm is capable to provide superior results for House, MRI and PAN image based on the objective metrics. The proposed approach and SBF both perform well on PAN image; however, our PSNR performance is best when the noise level rises from low to high levels. Altogether, PSNR performance varies dramatically with rising noise levels for all denoising methods except ours. As a result, our algorithm is capable to provide stable and consistent performance across the wide range of noise levels. As we
progress from standard deviation 10 to 50, the PSNR rates for methods other than our proposed method drop dramatically. For example, at $\sigma$ (standard deviation) 10 and 50, the PSNR value for House and MRI image in SBF decreases from 33.23 to 15.14 and 32.18 to 15.13, respectively, resulting in a difference of 18.09 and 17.05. For image House, MRI and PAN, the difference between PSNR value on $\sigma$ (standard deviation) 10 and 50 for our algorithm is less than other methods. In case of House, MRI and PAN image, however, the difference between PANR value on $\sigma$ (standard deviation) 10 and 50 for NLGRTV and TV1 had less differences, but their total PSNR performance is significantly low when compared to the other approaches. Bitonic and RBF had the least differences in PSNR values for image House, MRI and PAN. However, on standard deviation of 10 to 50, the overall PSNR value for House, MRI, and PAN image with our method is more than other comparative approaches. Therefore, the key benefits of our algorithm are being able to exhibit consistent performance with low noise contents. Our proposed technology has a far lower retardation rate than current denoising strategies. As a result, our algorithm may be used to deal with a wide range of noise levels. Execution time of proposed algorithm was found to be 4.25 s. Stage 1 and 2 denoising process takes 2.45 s and 2.00 s, respectively. This can be further lowered by using specialised hardware with the high configuration. Also, our proposed method exhibits faster experimental operation than other comparative algorithms and can be used for effective denoising process for numerous image datasets.
6 Conclusion

In this paper, we introduce an effective denoising algorithm by the decomposition of the image in coarser and finer layers and their subsequent processing. The proposed method maintains edges in the images in case of low to high noise levels. In this method, the advantages of both spatial and transform domain techniques are employed to handle the challenges of increasing noise levels in various image datasets. In comparison to SBF, MRF, RBF, NLFMT, GBFMT, and bitonic filter, the proposed method exhibits high stability and consistency for different noise levels. The proposed method shows comparable performance in case of low noise level; however, it has shown great potential to perform much better performance at moderate to high noise levels. The proposed algorithm is capable to reduce noise while simultaneously preserving the edges in the images. When there is an unknown

![Fig. 21 PAN image at σ = 50, denoising result a NLGRTV, b Ker. Reg., c TV1, d Bitonic, e NLFMT, f GBFMT, g RBF, h MRF, i SBF, j Proposed](image)

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**Fig. 21** PAN image at $\sigma = 50$, denoising result a NLGRTV, b Ker. Reg., c TV1, d Bitonic, e NLFMT, f GBFMT, g RBF, h MRF, i SBF, j Proposed
quantity of noise in different types of image datasets, the proposed method can be used as single denoising solution.

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Declarations

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