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Wavelet Based De-noising Using Logarithmic Shrinkage Function

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Abstract Noise in signals and images can be removed through different de-noising techniques such as mean filtering, median filtering, total variation and filtered variation techniques etc. Wavelet based de-noising is one of the major techniques used for noise removal. In the first part of our work, wavelet transform based logarithmic shrinkage technique is used for de-noising of images, corrupted by noise (during under-sampling in the frequency domain). The logarithmic shrinkage technique is applied to under-sampled Shepp–Logan Phantom image. Experimental results show that the logarithmic shrinkage technique is 7–10% better in PSNR values than the existing classical techniques. In the second part of our work we de-noise the noisy, under-sampled phantom image, having salt and pepper, Gaussian, speckle and Poisson noises through the four thresholding techniques and compute their correlations with the original image. They give the correlation values close to the noisy image. By applying median or wiener filter in parallel with the thresholding techniques, we get 30–35% better results than only applying the thresholding techniques individually. So, in the second part we recover and de-noise the sparse under-sampled images by the combination of shrinkage functions and median filtering or wiener filtering.

Keywords Wavelet transform · Sparsity · Compressed sensing · Shrinkage functions · Logarithmic shrinkage · Image de-noising · Impulsive noises · Median and wiener filtering

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1 Introduction

In signal and image processing, sparsity and compressed sensing provide relief in storage and transmission of the data. Signals have sparse representations in some transform domain such as Fourier Transform, Discrete Cosine Transform (DCT) and Wavelet Transform etc. During under-sampling and transformation the data is corrupted by under-sampling noise, which can be removed through different thresholding techniques. But in case of impulsive noise we need some other techniques in combination with the thresholding techniques. Different techniques are used for removal of noise, such as mean filtering [1], median filtering [2], total variation de-noising (TVD) [3] and filtered variation de-noising (FVD) [4] etc. Wavelet based de-noising is the most reliable technique due to its sparsity applications [5].

Wavelet based de-noising is important for its sparsity applications. It removes the noise significantly, gives high resolution of signals (or images) and affects the signal of concern to a very small extent. It can be used in three ways, such as wavelet de-noising using shrinkage functions [6]. Wavelet de-noising based on detecting the local maxima of the wavelet transform [7] and the third one is based on the correlation of the wavelet coefficients [8]. In the above three wavelet based de-noising techniques the most widely used technique is wavelet based de-noising using shrinkage functions. Most of the under-sampling noise can be removed from the signal (images) through this technique [9], [10].

Wavelet based thresholding technique consists of some classical and the recently introduced shrinkage functions. D.L. Donoho used hard shrinkage function for the first time. According to this rule the coefficients below the threshold level are discarded while keep the remaining unchanged. Another form of hard shrinkage function was proposed later by Donoho in 1995, called soft shrinkage function [11]. Later on a new shrinkage function named garrote, was examined by Gao in his work [12]. Compressed sensing techniques have many applications in the field of engineering and technology [16–19]. Although these all shrinkage functions produce good results but still there are some problems which could not be handled through the classical shrinkage functions. A new proposed shrinkage function with some modifications called logarithmic shrinkage function is used in this work for images recovery and de-noising. Various techniques for de-noising and regularization use the Tychonov penalty to estimate the signal from degraded data. Actually an attempt is made to solve the optimization problem,

$$\operatorname{argmin}\frac{1}{2}\|\mathbf{x}-\mathbf{y}\|_2^2+\lambda\frac{1}{2}\|\mathbf{x}\|_2^2 \tag{1}$$

This equation has a close form solution as given by $\hat{\mathbf{x}} = \frac{1}{1+\lambda}\mathbf{y}$ where "$\mathbf{x}$" is the original signal, "$\hat{\mathbf{x}}$" is the estimated signal, "$\mathbf{y}$" is the noisy signal and "λ" is the regularization parameter.

In this paper, we have compared the four thresholding techniques for recovery of under-sampled sparse images and also use these techniques in combination with median filtering and wiener filtering to recover the sparse images, degraded by salt and pepper, Gaussian, speckle and Poisson noises. In the first portion of our work, we take the wavelet transform of under-sampled Shepp–Logan Phantom image, apply the four thresholding techniques individually and then recover the image by taking the Inverse Wavelet Transform of the thresholded image. Proposed shrinkage function shines with the best results and gives high PSNR values as compare to hard, garrote and soft shrinkage functions. In the second part of our work, we take Shepp–Logan Phantom image and add salt and pepper (impulsive) noise to it. Taking the wavelet transform of the noisy image, threshold it and then iteratively recover the sparse image through hard, soft, garrote and proposed shrinkage functions. Through these techniques we can recover the sparse images but cannot satisfactorily de-noise them, when they are corrupted by impulsive noise, that's why we apply median filtering in addition with the thresholding techniques to get better results. The Images corrupted by Gaussian, Speckle and Poisson noises are also recovered and de-noised successfully through the proposed technique in parallel with the wiener filtering.

Basically we solved the following optimization problem for de-noising and regularization as follows,

$$\operatorname{argmin}\frac{1}{2}\|\mathrm{x}-\mathbf{y}\|_2^2+\lambda\frac{1}{2}\|\mathbf{x}\|_1 \tag{2}$$

We have applied iterative hard, garrote, soft and proposed shrinkage functions. Let $\hat{X}_{\mathrm{u}}$ is the under-sampled Fourier transform of "$\hat{x}$". At the start we suppose that $\hat{\mathrm{X}}_0 = \mathrm{Y}$, the steps of the algorithm are given as follows:

(1) Compute the inverse Fourier Transform of $\hat{\mathrm{X}}$ as $\hat{x}_i = F'(\hat{X}_i)$.
(2) Perform Wavelet transform to obtain sub-bands coefficients.
(3) Threshold all low frequency sub-band coefficients using certain shrinkage function in the Wavelet domain $\hat{x}_t = Thresh\ (W * \hat{x}_i,\ \lambda)$.
(4) Compute the inverse Wavelet transform to recover the noisy image $\hat{x}_i = W' * \hat{x}_i$.
(5) Compute the Fourier transform $\hat{X}_i = F(\hat{x}_i)$.
(6) Enforce data consistency in the transform domain X = X (Y = = 0) + Y.
(7) Run the iterations until $\|\hat{x}_{i+1} - \hat{x}_i\| < \varepsilon$.
where "ε" is stopping criteria. We apply the same procedure for garrote, soft and proposed shrinkage functions. The above method is a Projection onto Convex Sets (POCS) type algorithm. We apply twenty iterations to force the data consistency and get the satisfactory results. We compare the thresholding techniques by means of PSNR. Proposed shrinkage function gives the best results due to its flexibility. Remaining paper is organized as follows. Section 2 discusses the compressed sensing, Sect. 3 gives the proposed technique for noisy images, and Sect. 4 establishes the results. Conclusions are given in Sect. 5 followed by references.

2 Compressed Sensing and Its Recovery Techniques

Besides the other recovery and wavelet de-noising techniques, thresholding is the simplest technique through which the signal (or image) of interest may be recovered and de-noised with great accuracy. By means of thresholding the under-sampling noise is removed up to a very good extent. For the signal (or images) corrupted by both the under-sampling and impulsive noise median or wiener filtering in parallel with the thresholding techniques may be used. The three classical shrinkage functions along with the proposed technique for the recovery of sparse signals are given with proper mathematical and graphical representations in this section.

2.1 Hard Thresholding

Hard thresholding works on the principle of keep or kill rule. It removes the wavelet coefficients whose absolute values are below the threshold value and keep the remaining. It doesn't change the values of coefficients above the threshold value [13]. Hard shrinkage function is shown in Fig. 1a and is formulated as:

$$\mathbf{x_{ht}} = \left\{ \begin{array}{ll} 0 & \text{if } |\mathrm{x}| \leq \lambda \\ \mathrm{x} & \text{if } |\mathrm{x}| > \lambda \end{array} \right\} \tag{3}$$

2.2 Garrote Thresholding

Garrote thresholding adopts a modest way between hard and soft thresholding, and is a good compromise between hard and soft thresholding. It is more flexible than hard threshold and continuous like soft threshold, therefore it is more stable than hard threshold and soft threshold [14]. Garrote shrinkage function is depicted in Fig. 1b and is represented as:

$$\mathbf{x_{gt}} = \left\{ \begin{array}{ll} 0 & \text{if } |\mathrm{x}| \leq \lambda \\ \mathrm{x} - \dfrac{\lambda 2}{\mathrm{x}} & \text{if } |\mathrm{x}| > \lambda \end{array} \right\} \tag{4}$$

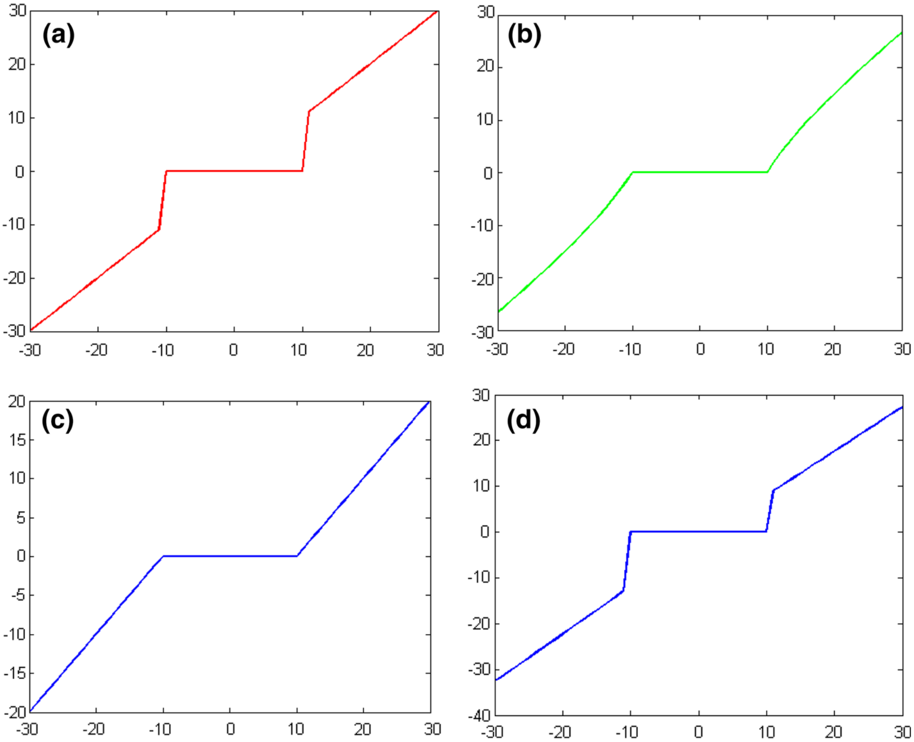


Fig. 1 **a** Hard shrinkage function, **b** garrote shrinkage function, **c** soft shrinkage function, **d** proposed shrinkage function

2.3 Soft Thresholding

Actually soft threshold is an extension of hard threshold. It is continuous shrinkage function, produces better results than hard and garrote threshold in our experiments [15]. Soft shrinkage function is shown in Fig. 1c and is formulated as follows:

$$\mathbf{x_{st}} = \left\{ \begin{array}{ll} 0 & \text{if } |\mathrm{x}| \leq \lambda \\ |\mathrm{x}| - \mathrm{s}\,\log\left(1 + \frac{|\mathrm{x}|}{\mathrm{s}}\right) & \text{if } |\mathrm{x}| > \lambda \end{array} \right\} \tag{5}$$

Equation 5 is compact form of soft shrinkage function.

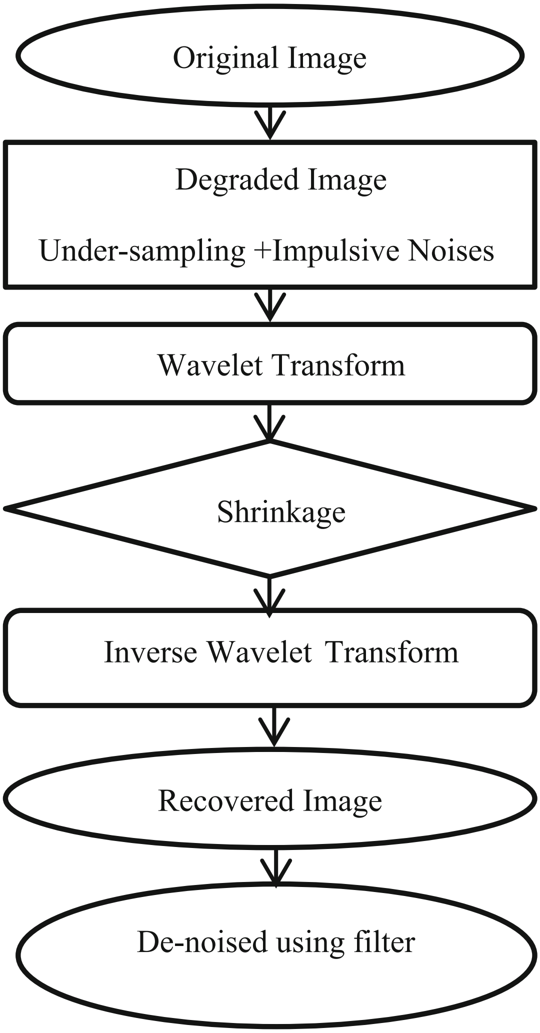


Fig. 2 Flow chart of the proposed technique

2.4 Proposed Thresholding

The previous three techniques are used continuously from a few decades. This is a new shrinkage function. It produces the best results due to the usage of "log" function. The proposed shrinkage function is depicted in Fig. 1d. The mathematical form of the proposed function is given by

$$\mathbf{x_{pt}} = \left\{ \begin{array}{ll} 0 & \text{if } |\mathrm{x}| \leq \lambda \\ |\mathrm{x}| - \mathrm{s}\,\log\left(1 + \frac{|\mathrm{x}|}{\mathrm{s}}\right) & \text{if } |\mathrm{x}| > \lambda \end{array} \right\} \tag{6}$$

The values of "s" are small positive constants. As Eq. (2), an optimization problem and the thresholding functions try to find the global minima. In the case of logarithmic shrinkage function, we find local minima instead of global minima. This is an iterative $l1$-norm approach. Due to direct relation with $l1$-norm it produces better results in recovery than soft thresholding and is also better in performance than hard thresholding due to the discontinuity of hard shrinkage function. l_1-*norm* is a pointy function and having a great ability to provide the sparse solution. In case of l_2-*norm*, we can find pseudo inverse but having no sparsity while in case of l_0-*norm*, we can recover the exact sparse signal but solving it, is NP-complete. It need exhaust search, all $\binom{N}{K}$ are non-zero coefficients.

Logarithmic function is the extension of exponential function. The exponential functions have derivatives exist at origin. That's why the proposed function produces better results for sparse signals recovery. For more flexibility in Eq. 6 (3d) we can select two different values of thresholding for positive and negative values of "x". By applying the wavelet transform, the total energy of the signal (or image) is spread to only a few coefficients and the remaining is lowered in amplitude. The proposed technique assigns the non-negative values to the components of the signal (or image) by taking the absolute values of the components. The reasons behind applying the proposed wavelet based thresholding technique is to discard all the components having values lesser than certain threshold value irrespective of their signs. Then well reconstruct the under-sampled signal (or image) from the high amplitude components only. The proposed technique produce enhanced results as compared to the soft, hard and garrote thresholding techniques because of its adoptive behavior to both the negative and positive values at the same time.

3 Proposed Model for Noisy Images

In addition with the sparse images recovery in Sect. 2, by means of wavelet based thresholding, we de-noise the phantom image, corrupted by impulsive noises (salt and pepper, Gaussian, speckle and Poisson) through median filtering or wiener filtering,

Table 1 PSNR values in dB

Shepp–Logan phantom image		
Shrinkage functions	λ	PSNR values
Hard	0.35	81.6
Garrote	0.20	83.4
Soft	0.07	85.5
Proposed	0.10	87.0

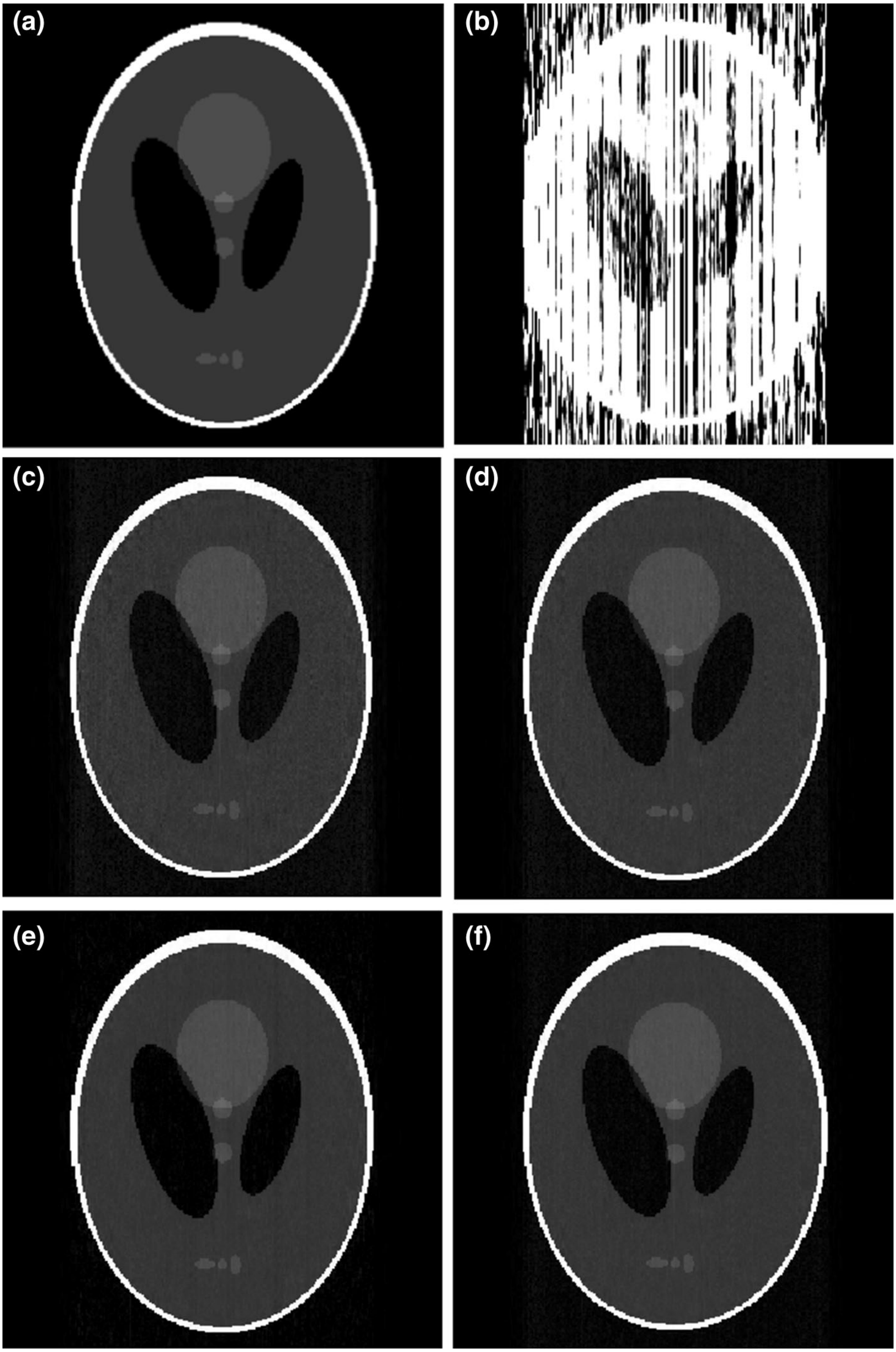


Fig. 3 Original phantom, noisy and de-noised images. **a** Original image, **b** noisy image, **c** de-noisy image, hard thresholding. **d** de-noisy image, garrote thresholding, **e** de-noisy image, soft thresholding and **f** de-noisy image, proposed method

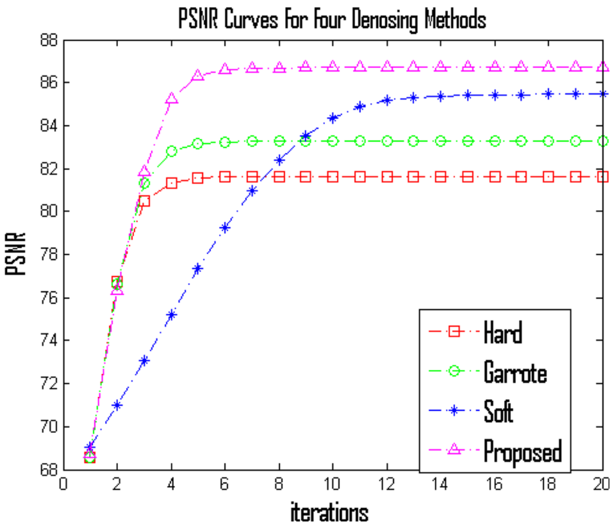


Fig. 4 PSNR curves for de-noising of phantom

because only thresholding is very less effective in case of impulsive noises and gives the correlation values of the recovered images closed to the noisy image. In signal and image processing median filter is frequently used for de-noising of signals and images because of its edge preserving properties. But in this work, we use thresholding technique in addition with median filter to recover and de-noised sparse images. We apply wavelet based thresholding techniques, by means of which we recover the sparse images and then apply median filter or wiener filter to eliminate the impulsive noises (salt and pepper, Gaussian, speckle and Poisson) from the images. Flow chart of the technique for sparse and noisy images recovery and de-noising is given in Fig. 2.

The novelty brought in the wavelet de-noising through the threhsolding techniques enhanced the performance of the recovery and de-noising. In the de-noising case where the signal (or image) is corrupted by impulsive noises along with the under-sampling noise, median or wiener filtering is used in parallel with the thresholding techniques. The original phantom image is under-sampled and corrupted (or degraded) by the impulsive noise. After applying the Wavelet Transform to get enough sparsity. As a special case of Wavelet Transform, Daubechies (4,4) Wavelet Transform is used. Iterative shrinkage functions are applied to remove the noise contents from the signal (or image). Only shrinkage functions are enough efficient to remove the under sampling noise but the signal (or image) recovered is still no satisfactory. For the removal of impulsive noise this work apply median filtering in case of salt and pepper noise while wiener filtering in case of Gaussian, Speckle and Poisson Noises. The methods used are very efficient and reliable in both cases either the noise is only under-sampling noise or is a mixture of under-sampling and impulsive noises.

The gains of using the Wavelet Transform or some other transforms are the nature of the transform to bring sparsity to the signal. A signal may not be sparse in one domain but when transform to some other domain must be sparse enough. That is the phantom images in the specific case are not sparse in spatial domain but when transformed to the Wavelet Transform become sparse and make the computation simple. After the necessary operations, the under-sampled images are recovered back through the shrinkage functions and

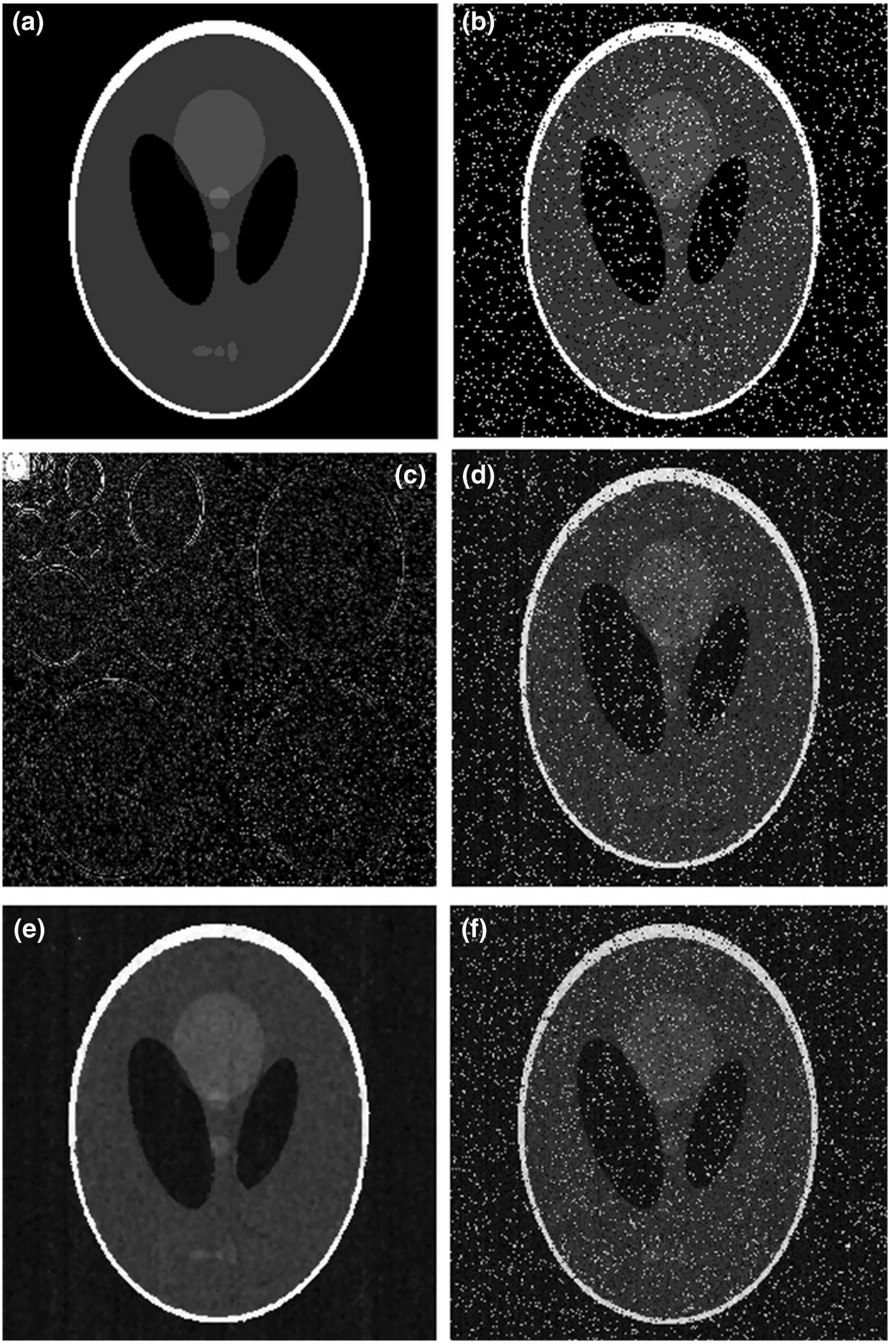


Fig. 5 Original, noisy (salt and pepper noise) and de-noised phantom images. **a** Original image, **b** noisy (salt and pepper noise), **c** wavelets of the noisy image, **d** recovered image, soft thresholding, **e** de-noised image, median filter + soft, **f** recovered image, hard thresholding, **g** de-noised image, median + hard, **h** recovered image, garrote thresholding, **i** de-noised image, median + garrote, **j** recovered image, proposed shrinkage, and **k** de-noised image, median + proposed

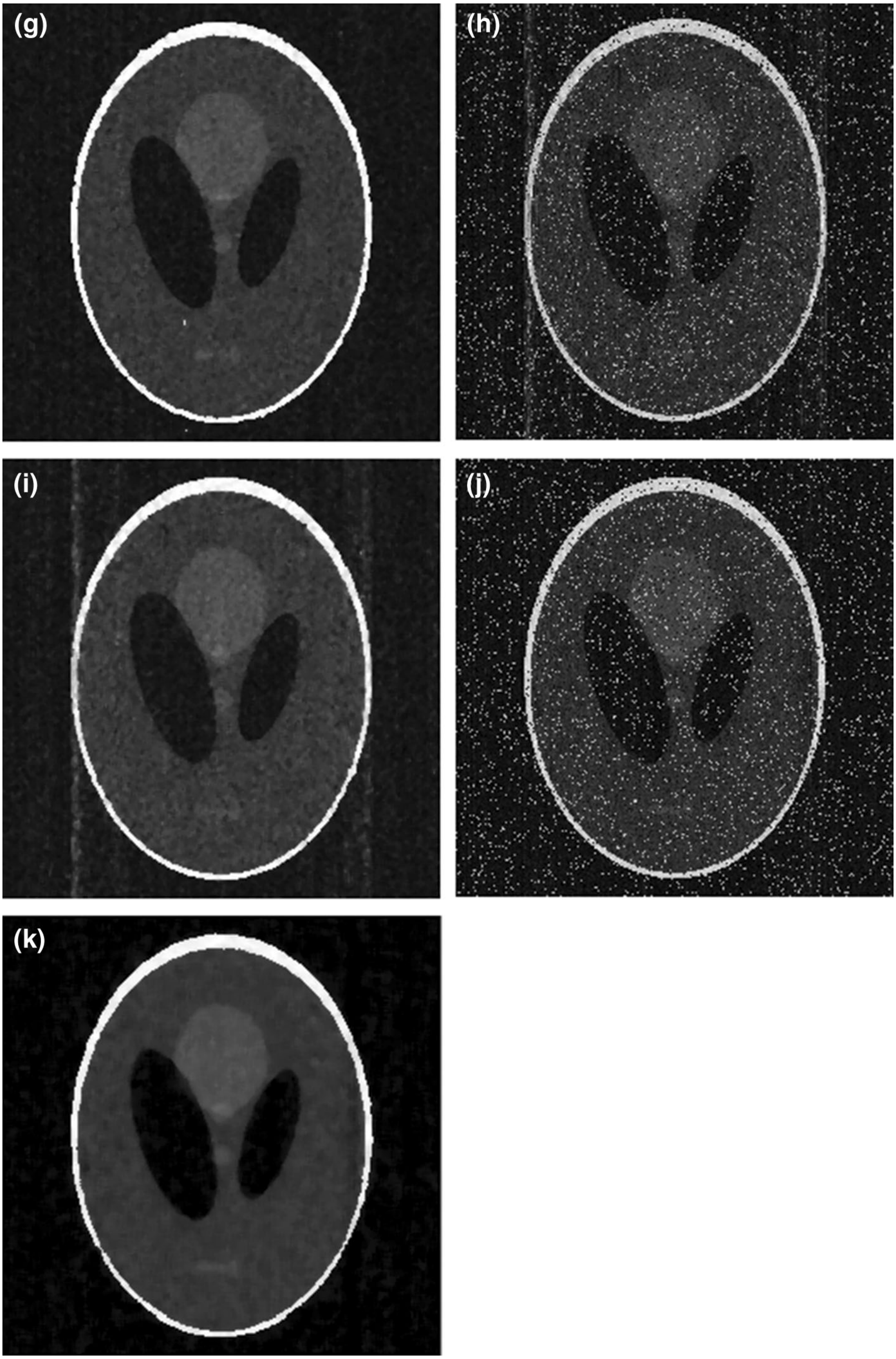


Fig. 5 continued

Table 2 Correlation values

Salt and pepper noise	Noise density	0.10
Correlations of the noisy and de-noised images with the original image. Hard threshold (H), soft (S), garrote (G), proposed (P) and median filtering(MF)	Noisy	0.6884
	S	0.6966
	S + MF	0.9761
	H	0.6865
	H+MF	0.9681
	G	0.6786
	G + MF	0.9551
	P	0.7046
	P + MF	0.9853

de-noised. Filters other than median and wiener filtering may be use but keeping in mind the requirement to preserve edges.

Sparsity has more applications in the field of medical imaging, where the time is the most important factor. That is MRI (Magnetic Resonance Imaging) and ultrasound. Due to the use of strong magnetic field and radio waves to take the images of the under investigation person, MRI badly affects the body. For the purpose of reduction of time, sparse signal applications are used to reduce the time inside the MRI machine and process the images to get the required results.

4 Results and Discussion

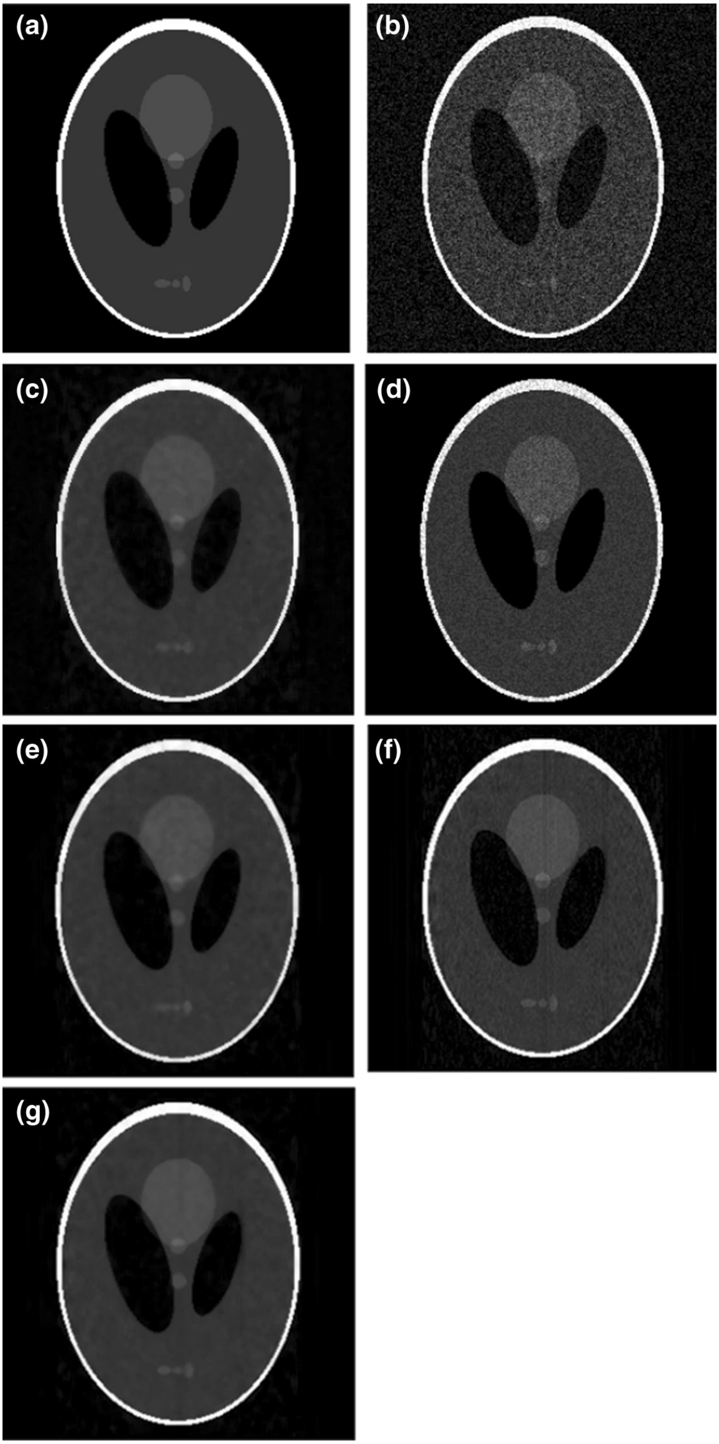
We present four thresholding techniques for image de-noising using wavelet transform. We take Shepp–Logan Phantom image of size 256 × 256. We individually apply the four shrinkage functions on Shepp–Logan Phantom. Performance of the techniques is judged by the PSNR values and correlation values.

PSNR of the noisy Shepp–Logan Phantom image is 68 dB. The PSNR value achieved by hard, garrote and soft shrinkage functions are 81.5, 83.4 and 85.5 dB respectively, while the PSNR value achieved by the proposed technique is 87.0 dB, which is greater than the other three techniques.

For phantom image, hard threshold gives satisfactory results at "$\lambda = 0.35$", garrote threshold is comparatively better at $\lambda = 0.20$ from hard while soft threshold shows the best results at "$\lambda = 0.070$". The proposed shrinkage function gives 87.0 dB, which is the best of all. The values of PSNR and λ for hard, garrote, soft and proposed methods are given in Table 1.

From the behavior of shrinkage functions it is clear that the proposed shrinkage function is the best among the other shrinkage functions, followed by soft, garrote and hard. We can give different values to "s". This is the additional parameter along with the "log function" which makes the proposed technique more flexible among the others.

The original and recovered images through the thresholding techniques are given in Fig. 3. Table 1 shows the PSNR values of the four shrinkage functions. The PSNR curves of them are given in Fig. 4.


(a)
(b)
(c)
(d)
(e)
(f)
(g)

◀**Fig. 6** Original, noisy (Gaussian, Speckle and Poisson Noises) and de-noised phantom Images. The original phantom image, the noisy (Gaussian noise), de-noised (Gaussian noise), noisy (Speckle noise), de-noised (Speckle noise), noisy (Poisson noise) and de-noised (Poisson noise) images are respectively given as **a**, **b**, **c**, **d**, **e**, **f** and **g** above

In the second portion of our work we apply median or wiener filtering in parallel with the thresholding techniques. We first apply the shrinkage functions on the sparse noisy images through which we recover the images but still having the impulsive "salt and pepper" noise. Then we apply median filtering to eliminate the salt and pepper noise. This hybrid technique is very effective in case of proposed thresholding, and gives high correlation values as compared to the other three thresholding techniques. The noisy and de-noised images are given in Fig. 5. We have evaluated the images based on the correlation values. The correlations values of images de-noised through these techniques and through median filtering are given in Table 2. The same procedure is used for de-noising of images corrupted by Gaussian, Speckle and Poisson Noises. For the recovery and de-noising of the images, wiener filtering is used in parallel with the proposed technique. The results are given in Fig. 6.

The proposed algorithm is computationally more efficient than the others because it just takes ten iterations for full recovery as compared to the other three thresholding techniques which take twenty iterations. The required results of recovery and de-noising are achieved in only ten iterations.

5 Conclusion

This paper addresses the image de-noising problem and compares the performance of the three existing shrinkage functions with that of the proposed logarithmic shrinkage function. The four shrinkage functions are applied for recovery of images having under-sampling noise (in transform domain). We test the Shepp–Logan Phantom (256×256) images in our experiments. The proposed threshold technique removes the under-sampling (aliasing) noise significantly and shows the best results as compared to hard, garrote and soft threshold functions. The proposed technique produces 7–10% better results than the existing classical shrinkage functions. In the second part of our work, we compare the de-noising results of the four thresholding techniques with that of the median filtering or wiener filtering. We use median and wiener filtering for de-noising of sparse and noisy images recovered through soft, hard, garrote and proposed shrinkage functions. These four thresholding techniques remove the under-sampling noise from the images but are not significant in the case of impulsive noise, that's why we use median and wiener filtering in parallel with the thresholding techniques for sparse images corrupted by salt and pepper, Gaussian, Speckle and Poisson Noises. The thresholding techniques in parallel with the median or wiener filtering produce 30–35% better results than produced by ordinary thresholding techniques. Besides the algorithm is better in performance, it is computationally simple for recovery and de-noising because of using the sparsity measures. In just ten iterations the proposed algorithm produces better results. The function running time is 4.01 s while the other three takes more than 4.5 s.

Compliance with Ethical Standards

Conflict of interest The authors declare that there is no conflict of interests regarding the publication of this paper.

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