Efficient Approach for De-Speckling Medical Ultrasound Images Using Improved Adaptive Shock Filter

Anas F. Ahmed
Department of Computer Engineering
Al-Iraqia University
Baghdad, Iraq
anasfuad33eng@yahoo.com

Abstract

The problem of filtering medical images is regarded one of the most important challenges that researchers are competing to solve it, where the filtered image helps to get the correct diagnosis of the diseases. This paper introduces an effective approach for filtering the medical ultrasound images. The main type of noise which corrupts the ultrasound images is the speckle noise. There are many methods for de-speckling this type of images addressed by the researchers including classical filters such as Weiner, Kuan, and Lee and adaptive filters such as shock filter. The performance of the proposed approach of this paper is compared with these filters using three performance evaluation metrics: "Peak Signal to Noise Ratio (PSNR)", "Mean Square Error (MSE)", and "Universal Image Quality Index (UIQ)". The empirical results illustrate that the proposed approach outperforms better than the others in term of these evaluation criteria. The proposed approach at noise variance=0.5 achieved the following values: (PSNR=32.0847db, MSE= 0.0962, and UIQ= 0.9829).

Keywords: Shock filter, Weiner filter, Lee filter, and Kuan filter.

1. Introduction

Medical images, like ultrasound, X-rays, and magnetic resonance are very effective technologies for the diagnosis several illnesses. These technologies offer great benefits to the medical imaging field [1]. Ultrasonography (US) or ultrasound imaging is an attractive diagnostic imaging technology since it presents several advantages such as more practical, safe, economic, and real-time. The ultrasound imaging is helpful in the visual inspection of internal tissues, muscles, organs, and or in quantitative analysis to get measures which can be used as "Bio-markers" for diagnosis of illnesses. The ultrasound images suffer from corruption due to speckle noise. The speckle noise reduction methods are very necessary for precise clinical comprehension and quantitative measurements. There are many de-speckling algorithms have been proposed for enhancing the quality of ultrasound images which can be implemented either in the spatial domain or in the transform domain. The Kuan's filter, and Lee's filter are the most famous spatial filters that used to minimize the speckle noise [2]. The Weiner filter is one of the most important frequency domain filters which used for de-speckling the medical ultrasound images [3]. This paper consists of the following sections: section 2 presents explanation of speckle noise and its mathematical model, section 3 includes the classical de-speckling filters, section 4 describes the shock filter and its equations, section 5 defines the performance evaluation metrics, section 6 introduces the proposed filtering approach, section 7 offers the numerical solution of the proposed filtering approach, section 8 presents the results and discussion, and finally section 9 gives the conclusions of this paper.

2. Speckle Noise

The speckle noise degrades the medical US images [4]. Speckle is usually appears in "echogenic areas" of the US images in the pattern of a granular appearance that corrupts the texture of these images [5,6]. This noise is danger, because it limits the vision of ailments, especially in the images that have low level of contrast [1]. It is necessary to model this type of noise carefully. The following model is used for images degraded with speckle [1]:

$$H(x,y)= G(x,y).\ \eta_p(x,y) + \eta_a(x,y) \qquad ..(1)$$

where:

H(x,y): Noisy image, G (x,y): Noise free image, $\eta_p(x,y), \eta_a(x,y)$: Multiplicative and additive noise functions. The additive noise is much less than the multiplicative noise, therefore (1) can be approximated as follows [1]:

$$H(x,y)= G(x,y)\ .\ \eta_p(x,y) \qquad ..(2)$$

3. Classical De-speckling Filters

This section presents a brief description of the well known filters which have been used to de-speckle the ultrasound images such as Lee, Kuan, and Weiner filters.

3.1 Lee Filter

This filter depends on the method that the smoothing is implemented on the area that has a little variance; therefore there is no smoothing near the edges of the images. By assuming that the image can be modeled as the following [7]:

$$Y_{xy}= \overline{K} + W * (C- \overline{K}) \qquad ..(3)$$

where :

Y_{xy}: The filtered gray scale value of the pixel at (x,y), K: Kernal value, $\overline{K}$: Mean intensity value of K, and C: The center pixel. The difference between C and $\overline{K}$ is determined and multiplied by the weighting function W [7]:

$$W=\frac{\sigma_k^2}{\sigma_k^2+\sigma^2} \quad ..(4)$$

where:

σ_k^2: The variance of the pixels and can be calculated using (5) [7]:

$$\sigma_k^2 = \frac{1}{M^2} \sum_{\alpha,\beta=0}^{M-1} (K_{\alpha\beta} - \overline{K})^2 \quad ..(5)$$

where:

M*M: The size of kernal, $K_{\alpha\beta}$: Pixel value inside the kernal at indices α and β, and σ^2: Image variance which can be determined using (6) [7]:

$$\sigma^2 = \frac{1}{N^2} \sum_{x,y=0}^{N-1} (X_{xy} - \overline{U})^2 \quad ..(6)$$

where:

$\overline{U}$: The mean intensity value of the image U.

N*N: The size of image U.

3.2 Kuan Filter

This filter transforms the multiplicative speckle noise model into additive model. The weighting function W of the Kuan filter can be calculated using (7) [7]:

$$W=\frac{(1-c_u / c_i)}{(1+c_u)} \quad ..(7)$$

where:

c_i: The variation coefficients of the image and can be evaluated using (8) [7]:

$$c_i = \sigma_k / \overline{K} \quad ..(8)$$

σ_k, and $\overline{K}$ defined previously in (3) and (4).

c_u : The predicted noise variation coefficients and can be determined using (9) [7]:

$$c_u = (ENL)^{\frac{-1}{2}} \quad ..(9)$$

Where the number of looks (ENL) is defined using (10) [7]:

$$ENL=[\frac{\overline{K}}{\sigma_k}]^2 \quad ..(10)$$

3.3 Weiner Filter

The frequency domain representation of this filter is given by (11) [8]:

$$\omega(m,n)=\frac{S_f(m,n)}{S_f(m,n)+S_N(m,n)} \quad ..(11)$$

where:

$S_f(m,n)$: Power spectrum of the original image, and $S_N(m,n)$: Power spectrum of the noise.

4. Adaptive Shock Filter

This filter was derived by Osher et al as given in (12) [9]. It uses time-dependent, non-linear partial differential equations (PDEs) i.e. u is a function of x, y, and t. Let x, y ∈ R, 0 ≤ t ∈ R , u (x,y,0) is the initial image, Then the PDEs achieve maximum principle and equal total variation of u for all $t \geq 0$.

$$\frac{\partial u}{\partial t} = -\text{sign}(u_{\eta\eta}).\, |\nabla u| \quad ..(12)$$

where:

∇u: Image gradient, η: the direction of ∇u, and $u_{\eta\eta}$: second order directional derivative of ∇u. The use of this filter causes a bogus edges and the "blocking effect" [10]. Mazorra and Alvarez improved the shock filter model as given in (13) [11]:

$$\frac{\partial u}{\partial t} = -\text{sign}(G_\sigma * u_{\eta\eta}).\, |\nabla u| + c_\xi u_{\xi\xi} \quad ..(13)$$

where:

G_σ: Gaussian function , $u_{\xi\xi}$: The former diffusion of the noise eliminator, and c_ξ : positive constant.

5. Performance Determination Metrics

The "Mean Square Error (MSE)", and "Peak Signal to Noise Ratio (PSNR)" determination metrics are used to measure the performance of filters quantitatively using (14), and (15) [1]:

$$MSE=\frac{1}{X.Y} \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} [P(x,y) - \overline{P}(x,y)]^2 \quad ..(14)$$

$$PSNR=10.\log_{10}(\frac{255^2}{MSE}) \quad ..(15)$$

where:

P: Original image, and $\overline{P}$: filtered image.

x,y: previously defined in (3).

The performance of the closest two filters is more analysed using an image quality metric called "Universal Image Quality Index", (UIQ). This index was derived by Zhou et al as follows [12]:

$$UIQ=\frac{4\sigma_{ef}\bar{e}\bar{f}}{(\sigma_e^2+\sigma_f^2)[\bar{e}^2+\bar{f}^2]} \quad ..(16)$$

$$\bar{e} = \frac{1}{N}\sum_{T=1}^{N} e_T \quad ..(17)$$

$$\bar{f} = \frac{1}{N}\sum_{T=1}^{N} f_T \quad ..(18)$$

$$\sigma_e^2 = \frac{1}{N-1}\sum_{T=1}^{N}(e_T - \bar{e})^2 \quad ..(19)$$

$$\sigma_f^2 = \frac{1}{N-1}\sum_{T=1}^{N}(f_T - \bar{f})^2 \quad ..(20)$$

$$\sigma_{ef}^2 = \frac{1}{N-1}\sum_{T=1}^{N}(e_T - \bar{e})(f_T - \bar{f}) \quad ..(21)$$

where:

e: Original image, f: test image, and T=1,2,..N. The optimal value of UIQ is 1.

6. Proposed Filtering Approach

This paper proposes an optimal adaptive shock filter. The weights of this filter adapted according to image gradient as well as they are continuous. The proposed filter can eliminate the image artifacts and the speckle noise efficiently. The mathematical expression of the proposed filter is given by (22), and (23):

$\frac{\partial u}{\partial t}$ = -(1- g(|∇u|)) tanh($G_\sigma *$ $u_{\eta\eta}$)|∇u|+c_ξ $u_{\xi\xi}$ ..(22)

The edging stop function g(|∇u|)=exp($\frac{-|\nabla u|^2}{c_\eta}$) ..(23)

where:

c_η, and c_ξ: Positive constants that control the forward diffusion and the weights of the shock filter. In this model the tanh(x) function is used rather than sign(x) function to guarantee the continuity and the strength of filter at the edges of the image. The sign(x) function used in (12), and (13) has three values (-1,0,1). The weights are similar around the inflection point which causes "sawtooth effect" around the edges. The curves of sign(x), and tanh(x) functions are shown in figure (1). In the proposed filter, the edge diffusion and the weights will be smaller when the gradient of image is larger, and the reverse is true. The weights of the proposed filter will adapt continuously with the gradient of image.

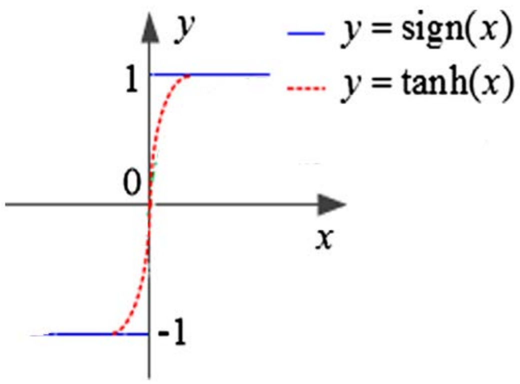

Figure 1: The comparison of sign(x), and tanh(x) curves.

7. Numerical Solution of the Proposed Filtering Approach

The finite difference approach is used to solve (22) as given in (24):

u^{n+1}= u^n+ Δt{c_ξ $u^n_{\xi\xi}$ - [1- g(|∇u^n|)] tanh($G_\sigma *$ $u_{\eta\eta}{}^n$) |∇u^n|} ..(24)

where:

Δt: The length of the step at each iteration.

$$u_{\eta\eta}=\frac{u_{xx}\ u_x^2+2\ u_{xy}u_xu_y+u_{yy}\ \ u_y^2}{u_x^2+u_y^2} \quad ..(25)$$

$$u_{\xi\xi}=\frac{u_{xx}\ u_y^2-2\ u_{xy}u_xu_y+u_{yy}\ \ u_x^2}{u_x^2+u_y^2} \quad ..(26)$$

where:

u_y, and u_x : The first order difference of y and x.

u_{xx}, u_{yy}, and u_{xy}: The second order difference of x and y. The magnitude of ∇u is determined using (27) [10]:

$$|\nabla u|=\frac{1}{h}\sqrt{O(u_x^+,u_x^-)^2+O(u_y^+,u_y^-)^2} \quad ..(27)$$

where:

$$O(q,r)=\begin{cases}\mathrm{sign}(q)\max(|q|,|r|), & qr>0\\ 0 & \text{others}\end{cases} \quad ..(28)$$

O (q,r): Approximate discretization of ∇u.

h: spatial step, u_x^+, u_y^+: forward difference in the direction of x and y, u_x^-, u_y^-: backward difference in direction of x and y. The forward and backward difference in x direction can be calculated using (29):

$$\begin{cases}u_x^+(i,j)=u(i+1,j)-u(i,j)\\ u_x^-(i,j)=u(i,j)-u(i-1,j)\end{cases} \quad ..(29)$$

where:

i, j: The coordinates x, y of image u.

The second order difference in x, and y directions can be determined using (30), and (31):

$$\begin{cases}u_{xx}(i,j)=u(i+1,j)+u(i-1,j)-2u(i,j)\\ u_{xy}(i,j)=[u_x(i,j+1)-u_x(i,j-1)]/2\\ u_{yy}(i,j)=u(i,j+1)+u(i,j-1)-2u(i,j)\end{cases} \quad ..(30)$$

$$\begin{cases}u_x(i,j)=\frac{u(i+1,j)-u(i-1,j)}{2}\\ u_y(i,j)=\frac{u(i,j+1)-u(i,j-1)}{2}\end{cases} \quad ..(31)$$

8. Results and Discussion

A comparative study is made between Lee, Weiner, Kuan, adaptive shock filters and the proposed filtering approach. The speckle noise is added to the original ultrasound image to determine the performance of each filter quantitatively. The noise variance is changed from 0.03 to 0.5. The process of adding speckle noise and varying the noise variance is implemented using (imnoise) function of the Matlab (R2013) program. The PSNR, and MSE are calculated for each value of noise variance. The Kuan, Weiner, and Lee filters are implemented with two different window sizes:(3*3), and (5*5). The number of iterations for the adaptive shock filter and the proposed filtering approach is thirty. After conducting several tests it is found that if the number of iterations is above thirty, the implementation consumes long time with no significant improvement of the results (three digits after the decimal point). The results demonstrate that the performance of the filters in the following order: proposed filtering approach, adaptive shock filter, Weiner (3*3), Kuan (5*5), Kuan (3*3), Lee (5*5), and finally Lee (3*3). Figure (2), and figure (3) show the performance of filters in term of MSE, and PSNR respectively. The higher value of PSNR, and the lowest value of MSE are scored for the proposed filtering approach and the adaptive shock filter proposed by [11]. The

UIQ is calculated for more comparison between them as shown in figure (4). The results illustrate that the suggested filtering approach has better performance than the shock filter. At very noisy environment (noise variance=0.5) the proposed filter attains the following values: (PSNR=32.0847db, MSE= 0.0962, and UIQ= 0.9829), while the shock filter proposed by [11] gives the following values: (PSNR=30.1312db, MSE= 0.1038, and UIQ= 0.9818) at the same noise environment. The original medical ultrasound image is shown in figure (5). The figures from (6) to (14) show samples of the visual comparison between the noisy image and the filtered image using adaptive shock filter and the proposed filtering approach for the noise variance values: 0.06, 0.1, and 0.5. Figure (15) shows the comparison of "sawtooth effect" between shock filter proposed by [11] and the proposed shock filter of this paper.

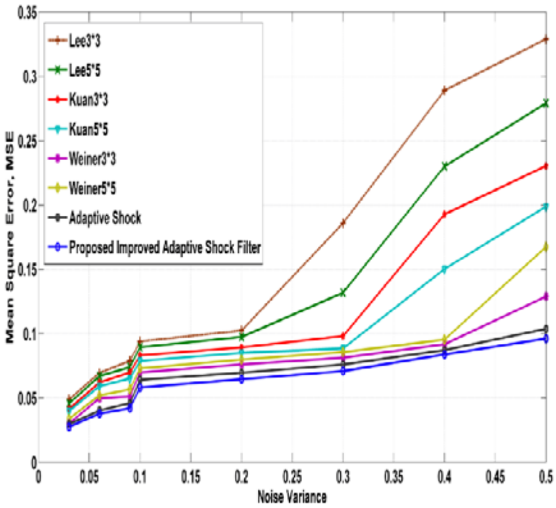

Figure 2: Performance comparison of the filters in term of MSE.

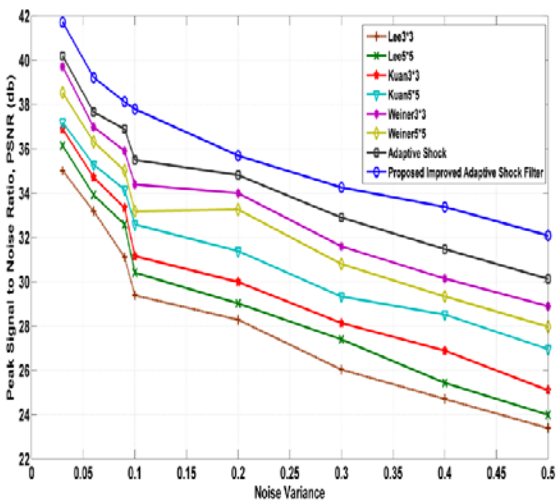

Figure 3: Performance comparison of the filters in term of PSNR.

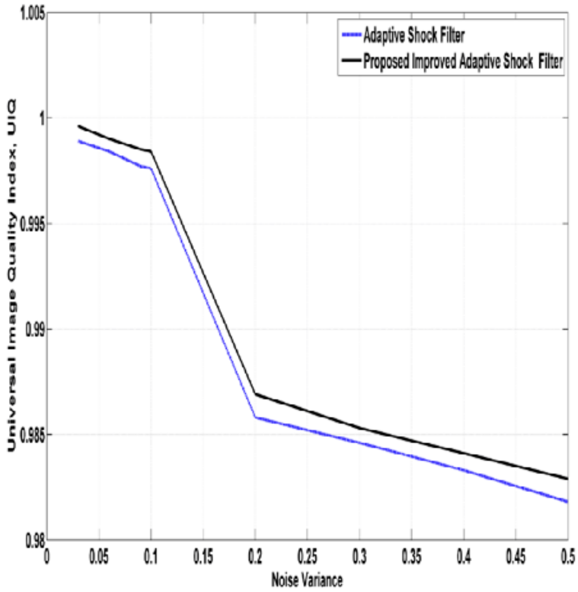

Figure 4: Performance comparison of the filters in term of UIQ.

Figure 5: Original medical ultrasound image.

Figure 6: Noisy image with noise variance=0.06.

Figure 7: Implementing adaptive shock filter to figure 6.

Figure 8: Implementing the proposed improved adaptive shock filter to figure 6.

Figure 9: Noisy image with noise variance=0.1.

Figure 10: Implementing adaptive shock filter to figure 9.

Figure 11: Implementing the proposed improved adaptive shock filter to figure 9.

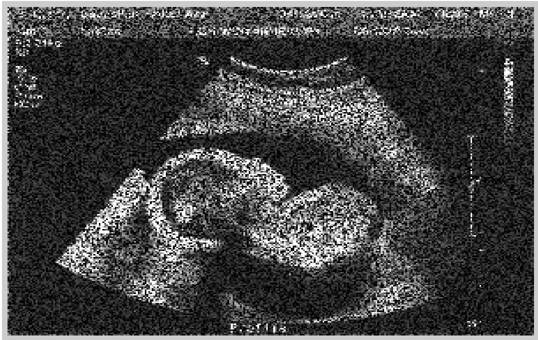

Figure 12: Noisy image with noise variance=0.5.

Figure 13: Implementing adaptive shock filter to figure 12.

Figure 14: Implementing the proposed improved adaptive shock filter to figure 12.

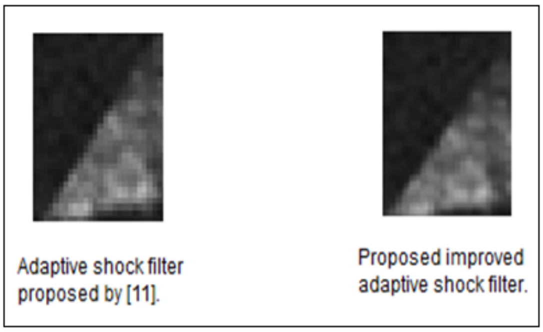

Figure 15: Sawtooth effect comparison.

9. Conclusions

This paper discussed the problem of speckle noise in the medical ultrasound images. An improved adaptive de-speckling filter is proposed to remove the speckle noise from these images. The performance of the proposed filter is compared with the filters presented in the literature. Depending on the obtained results it can be concluded that the proposed filter better than the others filters in term of quantitative and qualitative measurements as well as the visual assessments. Also, from the results it can be concluded that the improved adaptive shock filter can produce a smoother edges with less staircasing effect than the traditional shock filter. This reason has a great impact on obtaining a good filtered image with preserving its details, but it complicates the computations.

References

[1] Mateo, L., and Caballero, F., (2009), "Finding out general tendencies in speckle noise reduction in ultrasound images", ELSEVIER, Vol. 36, Issue. 4, pp. 7786–7797.

[2] Sudeep, V., Palanisamy, P., Rajan, J., Baradan, H., Saba L., Gupta, A., and Suri S., (2016), " Speckle reduction in medical ultrasound images using an unbiased non-local means method", ELSEVIER, Vol. 28, pp. 1-8.

[3] Bahateja, V., Singh, G., Srivastava, A. and Singh, J., (2014), "Speckle Reduction in Ultrasound Images Using an Improved Conductance Function Based on Anisotropic Diffusion", IEEE Int. Conf. Computing for Sustainable Global Development, pp. 619-624.

[4] Njeh, I. Sassi, B. Chtourou, K., and Hamada, A., (2011), "Speckle Noise Reduction in Breast Ultrasound Images: SMU Approach", IEEE Int. Conf. Systems, signals and systems, pp. 1-6.

[5] Kyriacou, C., Pattichis, C., Pattichis, M., Louizou, C., Christodoulou, C., Kakkos, K., and Nicolaides, A., (2010), "A Review of Noninvasive Ultrasound Image Processing Methods in the Analysis of Carotid Plaque Morphology for the Assessment of Stroke Risk", IEEE Trans. Information Technology in Biomedicine Vol. 14, No. 4, pp. 1027-1038.

[6] Cm, W., Yc, C., and Ks, H., (1992), "Texture features for classification of ultrasonic liver images", IEEE Trans. Medical Imaging, Vol .11, Issue. 2, pp. 141-152.

[7] Herimath, S., Akkasaligar, T., and Badiger, S., (2013), "Advancements and Breakthroughs in Ultrasound Imaging", INTECH, pp. 300.

[8] Suhaila, S., and Shimamura, T., (2010), "Power spectrum estimation method for image denoising by frequency domain Wiener filter", IEEE Int. Conf. Computer and Automation Engineering, Vol. 3, No. 1, pp. 608-612.

[9] Terebes, R., Borda, M., Germain, C., and Lavialle, O., "A Novel Shock Filter for Image Restoration and Enhancement", (2012), IEEE Int. Conf. Signal Processing, pp. 255-259.

[10] Battiato, S., Gallo, G., and Stanco, F., " Smart Interpolation by Anisotropic Diffusion", (2003), IEEE Int. Conf. Image Analysis and Processing, pp. 572-577.

[11] Alvarez, L., and Mazzora, L., (1994), " Signal and image restoration using shock filters and anisotropic diffusion", SIAM Journal, Vol. 31, Issue. 2, pp. 590-605.

[12] Wang, Z., and Bovic, C., (2002), "A Universal Image Quality Index", IEEE Letter. Signal Processing, Vol. 9, Issue. 3, pp. 81-84.

طريقة كفوءة لتصفية صورالموجات فوق الصوتية الطبية من التشويش الرقطي بأستخدام مصفي الصدمة المتكيف المحسن

أنس فؤاد أحمد
قسم هندسة الحاسوب/الجامعة العراقية
anasfuad33eng@yahoo.com

الخلاصة:
تعد مشكلة تصفية الصور الطبية من أهم التحديات التي يتنافس الباحثون لحلها، حيث ان الصورة التي يتم تصفيتها تساعد في الحصول على التشخيص الصحيح للأمراض. يقدم هذا البحث طريقة كفوءة لتصفية صور الموجات فوق الصوتية الطبية بأستخدام مصفي الصدمة المتكيف المحسن. يعد التشويش الرقطي (Speckle Noise) النوع الرئيسي للتشويش الذي يشوه صور الموجات فوق الصوتية. توجد العديد من الطرق للتخلص من هذا التشويش تم التطرق لها من قبل الباحثين منها المصفيات الكلاسيكية مثل وينر (Weiner) , كوان (Kuan) , ولي (Lee) والمصفيات المتكيفة مثل مصفي الصدمة (Shock Filter). تم مقارنة اداء الطريقة المقترحة في هذا البحث مع هذه المصفيات باستخدام ثلاث مقاييس للاداء: ذروة نسبة الاشارة الى الضوضاء (PSNR) ، معدل مربع الخطأ (MSE) ومعامل جودة الصورة العام (UIQ). اظهرت النتائج ان اداء الطريقه المقترحة افضل من الطرق الاخرى بدلالة هذه المعايير. حققت الطريقة المقترحة عند تباين ضوضاء (Noise Variance=0.5) القيم التالية: ذروة نسبة الاشارة الى الضوضاء (PSNR=32.0847db) , معدل مربع الخطأ (MSE=0.0962) و معامل جودة الصورة العام (UIQ=0.9829).