Medical Image Denoising with Wiener Filter and High Boost Filtering

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Abstract

The Wiener filter is widely used in image de-noising. It is used to reduce Gaussian noise. Although the Wiener filter removes noise from the image, it causes a loss of edge detail information, resulting in blurring of the image. The edge details are considered high-frequency components. The Wiener filter is unable to reconstruct these components. In this paper, the proposed filter based on the Wiener filter and the high-boost filter for medical images is presented. The proposed filter is applied to the degraded image. First, using Fourier Transformation, the degraded image and the high boost filter are converted in the frequency domain. Secondly, the wiener filter is applied to the image along with the high boost filter. Thirdly, the deconvolution process is achieved on the image with the high boost filter. Finally, to reconstruct the sharper image in the spatial domain, the inverse of the Fourier transformation is applied. The proposed filter works to suppress the additive noise at the same time. It can keep the image's edge details. Some focus operators are used, which are image contrast, gradient energy, histogram entropy, and spatial frequency, in order to test the proposed algorithm. Experimental results showed that the proposed filter gives good results compared with the traditional filters for medical images, especially dark images.

Keywords: Wiener filter, sharpen filter, high Boost filtering, Blind image deconvolution, image contrast.

فلتر Wiener وفلترة High Boost لتقليل ضوضاء الصورة الطبية

ندى جاسم حبيب

تقنيات المعلوماتية، الكلية التقنية الادارية، الجامعة التقنية الوسطى، بغداد، العراق

الخلاصة

يستعمل مرشح Wiener على نطاق واسع في إزالة ضوضاء الصورة. يستعمل لتقليل الضوضاء الغاوسية. على الرغم من أن مرشح Wiener يزيل التشويش من الصورة، إلا أنه يتسبب في فقدان معلومات تفاصيل الحافة، مما يؤدي إلى تشويش الصورة. تعتبر تفاصيل الحافة مكونات عالية التردد. مرشح Wiener غير قادر على إعادة بناء هذه المكونات. في هذا البحث، يتم تقديم المرشح المقترح على أساس ترشيح Wiener ومرشح التعزيز العالي للصور الطبية. يتم تطبيق المرشح المقترح على الصورة المتدهورة. أولاً ، يتم تحويل الصورة المتدهورة ومرشح التعزيز العالي في مجال التردد باستعمال تحويل فورييه. ثانيًا ، يتم تطبيق مرشح wiener على الصورة ومرشح التعزيز العالي. ثالثًا ، يتم تحقيق عملية deconvolution على الصورة ومرشح التعزيز

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العالي. أخيرًا ، لإعادة بناء الصورة الأكثر وضوحًا في المجال المكاني ، يتم تطبيق معكوس تحويل فورييه.
يعمل المرشح المقترح على منع الضوضاء المضافة في نفس الوقت، ويمكنه الاحتفاظ بتفاصيل حافة الصورة.
تستعمل بعض عوامل التركيز وهي تباين الصورة، وطاقة التدرج، و Entropy المدرج التكراري، والتردد المكاني
من أجل اختبار الخوارزمية المقترحة. أظهرت النتائج التجريبية أن المرشح المقترح يعطي نتائج جيدة مقارنة
بالمرشحات التقليدية للصور الطبية خاصة الصور المظلمة.

1. Introduction

The problem of removing noise or blur from images has been studied for a long time. However, this remains a challenging and open process because, from a mathematical point of view, noise or blur reduction in the image is a reversible problem and its solution is not unique. The purpose of removing noise from the image is to reduce the noise density ratio while reducing the loss of the original features of the image, in addition to improving the signal-to-noise ratio. There are a number of challenges to the process of removing noise from the image. First, the flat areas must be smooth. Second, the edges should not be distorted or blurred. Third, the texture should be preserved. Finally, artifacts should not be generated after the noise removal process [1].

The Wiener filter is widely used in image processing for noise suppression and enhancement. It can remove the additive noise and, at the same time, reflect the blurring [2]. However, Wiener filtering is a linear and shift-invariant filter scheme. One of the limitations of the Wiener filter is the degradation of the high-frequency components that leads to the smoothing of some of the image details. This means that it is not appropriate for images containing edges, because it generates blurred edges in the image [3, 4]. The improvement of edges in the image is of great importance in image processing, especially in medical images, because the human visual system uses the edges in the image as a key factor in understanding the contents of the image [4]. In this paper, a combination of Wiener filtering and high-boost filtering is proposed to improve the focus of edge details while removing noise from degraded medical images.

2. Related Works

Many researchers have suggested reducing noise and blur for degraded images by developing some noise removal filters, including the Wiener filter. In recent years, great achievements have been made in improving the performance of the Wiener filter for image de-noising, especially in the field of enhancement of medical images.

In modern medicine, which includes technical advances in imaging devices and imaging methodologies, the quality of the digital medical image has played an important role in achieving the best possible diagnosis. It is important that the medical image be sharp, clear, and free of noise. Therefore, removing noise from medical images is important in order to recover hidden details in the image data [5].

For the problems of multi-objective optimization [6], the authors proposed a denoising method based on the mean and Wiener filters, which are embedded in the algorithm of multi-objective optimization. The filters are used to remove noise from dominant solutions, as filters work to balance closeness and population diversity.

In the nuclear medicine method, before the gamma rays fall on the detector, the resulting images are exposed to noise due to scattering and attenuation. This leads to a decrease in image quality, low contrast, and high noise. In [7], the authors suggested combining the median filter

with the Wiener filter for the purpose of improving the degraded image. The value of the mask matrix in the Wiener filter is replaced by the median value to reduce the noise distribution in the image. This method improved the gamma image better than using traditional denoising methods.

For ultrasound images that are affected by speckle noise, in [8], the authors proposed a denoising technique to enhance the Wiener filter. This technique adapts the theory of Markov Random Field to model a noise-free image. This denoising technique was proposed to solve one of the limitations of the Wiener filter because the Wiener filter operates in the frequency domain and does not consider the local behavior of the image.

In urban areas, sometimes coherent noise signals occur repeatedly through traffic in a short period of time, which leads to the production of false propagation waves. In [9], the authors proposed a denoising filter using the Wiener filter and singular value decomposition to reduce spurious signals in cross-correlation functions for the purpose of reducing cross-distortions in the scattering image.

The authors of [10], proposed a denoising approach for influenced images by highly speckled noise using bacterial foraging optimization, wavelet transform, and wiener filter. The wavelet transform and the Wiener filter remove the noise from affected pixels as preprocessing. After processing, the bacterial foraging optimization algorithm is used to reduce the amount of error between the noisy image and the denoised image. It is used to improve fine details with an error rate of 0.0001.

The author [11] presented an image denoising technique based on the Wiener filter. This technique iteratively removes noise from the image in a multi-step manner. The denoising process stops when the energy of the image is adaptively achieved. The authors in [12] presented an image denoising technique based on a combination of the modified Median Wiener filter, Absolute Difference, and Mean filter to suppress the Gaussian noise in medical images. This method produces good results in terms of peak signal to noise ratio and mean square error. A Modified Weighted Average Filter was proposed in [13] for noise removal from medical images. Firstly, the noisy pixels are detected by using a mask. And then a filter is applied to compute the weights according to the correlation between the free pixels and noisy pixels. The authors in [14] presented two filters, which are the Wiener filter and the Kalman filter, to remove noise from electrocardiogram signals that are related to the functioning of the heart. The results showed that the Wiener filter is good for removing noise from the ECG signal.

Noise, edge, and texture are high-frequency components, so it is difficult to distinguish between them when performing noise removal from a noisy image. And the de-noised image can lose some useful information [1]. The process of removing noise from a degraded image to obtain high-quality data is an important challenge nowadays.

3. Method
3.1 Wiener Filter Concept
The two-dimensional (2D) Wiener filter (WF) is a linear filter which is considered one of the best known in the field of removing noise and improving degraded image quality [15]. The degraded image $g(x, y)$ can be expressed mathematically by the following equation No. 1 [2]:
$$g(x, y) = f(x, y) \otimes h(x, y) + \eta(x, y) \qquad (1)$$
, where $f(x, y)$ is the original (ideal) image, $h(x, y)$ is the degraded function, $\eta(x, y)$ is the additive noise, and "$\otimes$" is the convolution process which is a multiplication operation between

the pixels of the ideal image $f(x, y)$ and the pixels of degradation function $h(x, y)$. The de-convolution process is performed to recover the original image. The WF is a deconvolution filter which is used to estimate $\acute{f}$ of the ideal (original) image , so that the error between them can be calculated as [16]:

$$error^2 = \mathcal{E}\{(\acute{f} - f)^2\} \tag{2}$$

where $\mathcal{E}\{.\}$ is the expected value of the argument.

The Wiener filter is applied in the Fourier transform. The degraded image g_{xy} is converted into the Discrete Fourier Transform to obtain $\mathbb{G}_{uv}$ .The spectrum of the original image $\mathbb{S}$ is estimated by [17]:

$$\mathbb{S}_{uv} = \mathbb{W}_{uv} * \mathbb{G}_{uv} \tag{3}$$

The Wiener filter $(\mathbb{W})$ in the frequency domain can be calculated as follows:

$$\mathbb{W}_{uv} = \frac{\mathbb{H}^*_{uv}}{\mathbb{H}^*_{uv} \cdot \mathbb{H}_{uv} + (\frac{1}{\mathbb{SNR}})} \tag{4}$$

where $\mathbb{G}_{uv}$ is the Fourier transform of the input image, $\mathbb{H}^*_{uv}$ is the conjugate complex of $\mathbb{H}_{uv}$, $\mathbb{SNR}$ is the Signal Noise Ratio. $1/\mathbb{SNR}$ is the inverse of Signal Noise Ratio. The range of the $1/\mathbb{SNR}$ values is a constant value of range [0.0001- 0.01].

High-Boost filtering is one of the techniques that is used to highlight the important details and to improve some blurry regions in the image. It provides sharper and more visible edge information. High-pass and high-boost filters are two types of sharpening filters. A high-pass filter preserves the edge information and texture. The drawback of this filter is that it deletes the important low frequencies that are necessary to improve image quality.

The High-Boost filter is an extension of the high-pass filter. The High-Boost filter highlights the high-frequency details while preserving some low-frequency components. The High-Boost filter can be defined as [18]:

$$HighBoost\ filtered\ image = (A - 1) * original\ image + Highpass\ filtered\ image$$

When A=1, the result is a weighted version of the original image that is added to the high-pass details. When A>1, some details of the original image are added back to the high-pass filtered image.

Figure 1 shows examples of the High-Boost filtering masks for A>1.

0	-1	0	-1	-1	-1
-1	A+4	-1	-1	A+8	-1
0	-1	0	-1	-1	-1

Figure 1: High-Boost filtering masks

3.2 Blind Image Deconvolution

When the unknown blurring function and additive noise are unknown, blind image deconvolution can be applied. There is no information about the blurring function and the type of noise [19]. Blind image deconvolution aims to recover two convolved signals $\mathcal{F}$ (true image) and $\hbar$ from their convolved noisy image $\mathcal{g}$ (Point Spread Function PSF) which is responsible for the blurring of the true image. Generally, the blurring effect reaches to:

$$g(\mathcal{M}, \mathbb{N}) = \sum_{k=1}^{n1} \sum_{l=1}^{n1} \hbar(k, l) \mathcal{F}(\mathcal{M} - k, \mathbb{N} - l) + \omega(\mathcal{M}, \mathbb{N})$$
$$0 \le (\mathcal{M}, \mathbb{N}) \le N - 1$$

Where ω is noise with zero-mean, $n1 \times n1$ is PSF size. $\mathcal{g}, \mathcal{F}$, and ω are column vector of length N^2, which are built by stacking rows of matrices $\mathcal{g}, \mathcal{F}$, and ω [20].

4. Proposed Filter
Generally, images are often corrupted by random variations in intensity, illumination, or poor contrast. So, images are filtered for enhancement and smoothing. The traditional Wiener filter only suppresses noise, but cannot reconstruct the frequency components that have been degraded by noise. In this work, the proposed filter has two filters, which are the Wiener filter and the High Boost filter. We assume the degradation function, the blurring function $h(x, y)$, is known. The following steps explain the proposed filter algorithm:

Step1: Reading and converting ideal image $f(x, y)$ into a gray level image to obtain 2D image.

Step2: Reading the 3×3 High boost mask, k.

Step3: Adding some noise and blur to $f(x, y)$ using the noise and degradation functions to obtain a degraded image $g(x, y)$.

Step4: Applying Fourier transformation to $g(x, y)$ to obtain $\mathbb{G}_{uv}$ in the frequency domain.

Step5: Applying Fourier transformation to k to obtain $\mathbb{K}_{nn}$ in the frequency domain.

Step6: Applying the Wiener filter to $\mathbb{G}_{uv}$ using the following equation:
$$\mathbb{W}_g(u, v) = \frac{\mathbb{H}_{uv}^*}{\mathbb{H}_{uv}^* \cdot \mathbb{H}_{uv} + (\frac{1}{\mathbb{SNR}})} \cdot \mathbb{G}_{uv}$$

Step7: Applying the Wiener filter to $\mathbb{K}_{nn}$ using the following equation:
$$\mathbb{W}_k(n, n) = \frac{\mathbb{H}_{uv}^*}{\mathbb{H}_{uv}^* \cdot \mathbb{H}_{uv} + (\frac{1}{\mathbb{SNR}})} \mathbb{K}_{nn}$$
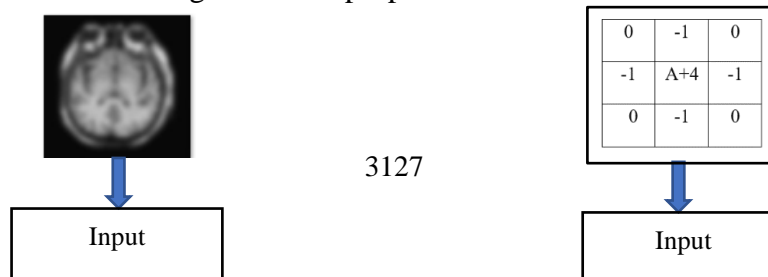
Step8: Applying deconvolution process to $\mathbb{W}_g$ and $\mathbb{W}_k$ to obtain the sharper image in the frequency domain.
$$\mathbb{W}_{gk} = \mathbb{W}_g * \mathbb{W}_k$$

Step9: Applying the inverse of Fourier Transformation (IFT) to reconstruct the sharper image in the spatial domain
$$\mathcal{f}(\text{x}, \text{y}) = \text{IFT}(\mathbb{W}_{gk})$$
Figure 2 illustrates the flow diagram of the proposed filter.

0	-1	0
-1	A+4	-1
0	-1	0

Input

Input

Figure 2: the flow diagram of the proposed filter.

Many filter operations for image enhancement are performed on the Fourier transform of the image due to its advantage. Applying filters to images in the Fourier transform is easy, faster, and more efficient for the computational operations [21, 22, 23].

5. Excremental Results
The performance of the proposed algorithm has been tested using different medical images such as MRI and CT images, which are collected from www.mathwork.com. The proposed algorithm performs the combination of the Wiener filtering and the High Boost filtering. In this work, the High Boost filtering can be implemented using the following kernels (k):
K1 = [0 -1 0; -1 6 -1; 0 -1 0], for A=2

K2 = [0 -1 0; -1 7 -1; 0 -1 0], for A=3
K3 = [0 -1 0; -1 5 -1; 0 -1 0], for A=1
To evaluate the performance of the proposed algorithm in terms of noise removal, blur, and the ability to highlight the edge, some different statistical metrics for the sharpness measurement were performed. The higher these metrics, the more focused the image is. First, the image Contrast (CONT) metric can be defined as follows:

$$CONT(x, y) = \sum_{i=x-1}^{x+1} \sum_{j=y-1}^{y+1} |f(x, y) - f(i, j)| \tag{5}$$

where $f(x, y)$ is the pixel of an image.
Second, the Gradient Energy (GE) metric is the sum of squares of the first derivative f'_x of the image f in the x direction and the first derivative f'_y of the image f in y can be defined as follows:

$$GE_{x,y=} \sum_{(i,j) \in \Omega(x,y)} (f'_x(i,j)^2 + f'_y(i,j)^2) \tag{6}$$

Third, the information content of the focused image is expected to increase. Histogram Entropy (HE) is used to calculate the amount of focus in the image. It can be defined as follows:

$$HE = -\sum_{k=1}^{L} P_k \log(P_k) \tag{7}$$

, where P_k is the probability of repetition of the k_{th} gray-level.
Finally, Spatial Frequency (SF) is defined by the following equation:

$$SF_{x,y} = \sqrt{\sum_{(i,j) \in \Omega(x,y)} f_x(i,j)^2 + \sum_{(i,j) \in \Omega(x,y)} f_y(i,j)^2} \tag{8}$$

where f_x and f_y denote the first derivatives of a fram in the X and Y direction, respectively. The experiments were conducted using MATLAB 2017b on a set of medical images of size 256×256. Figure 3 shows the original medical images (image1, image2, image3, ..., image10) which are used to test the performance of the proposed algorithm (Wiener-High Boost filter), the traditional Wiener filter, and the Blind image deconvolution technique. Figure 4 shows the noisy and blurred medical images (NB1, NB2, …, NB10) after adding the additive noise with variance equals=0.1 and Gaussian blur with sigma equals 5. Figure 5 illustrates the visual results for the denoised and deblurred images (W1, W2, …, W10) using the traditional Wiener filter. Figure 6 illustrates the visual results for the output images (B1, B2, …, B10) using the Blind Image deconvolution technique.
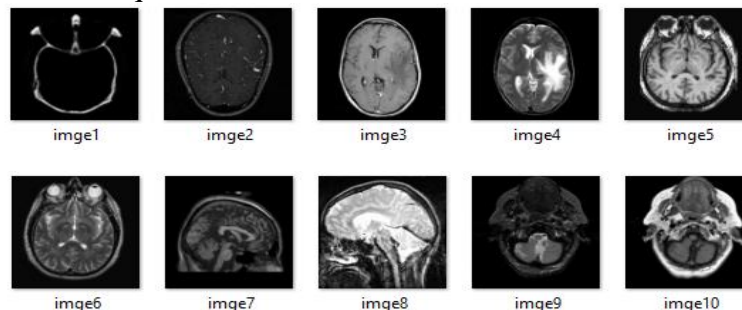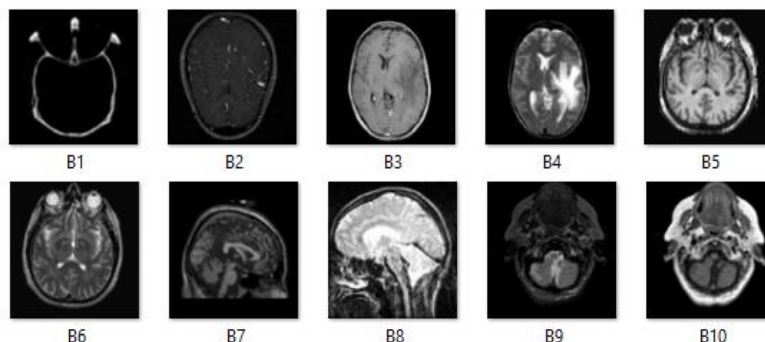

Figure 3: Medical image dataset
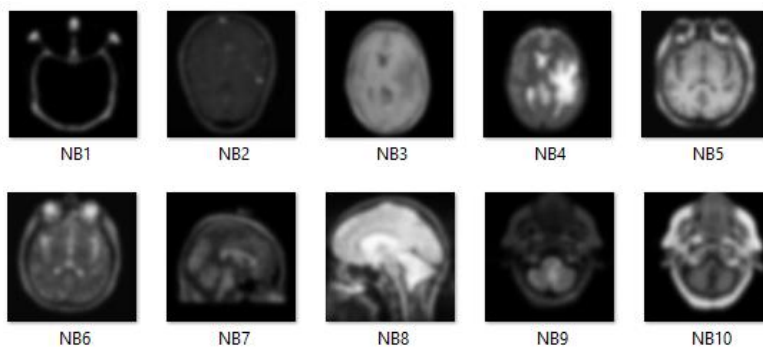
Figure 4: Noisy and blurred medical images.
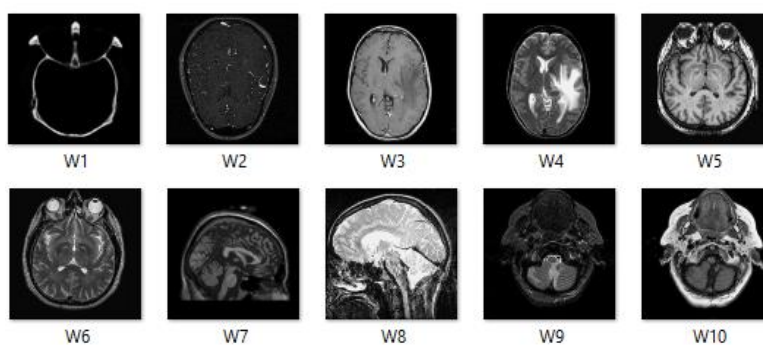
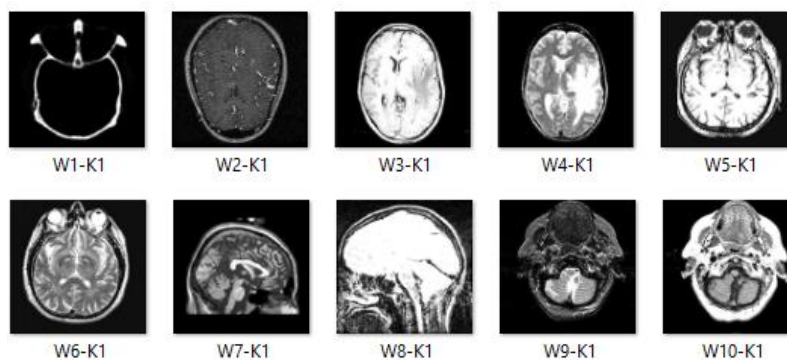**Figure 5:** Medical images resulting by the traditional Wiener filter.

Figure 6: the output images using Blind image deconvolution technique.

The following figures, from Figure 7 to Figure 9, show the visual results of the proposed algorithm with three different types of high boost masks.
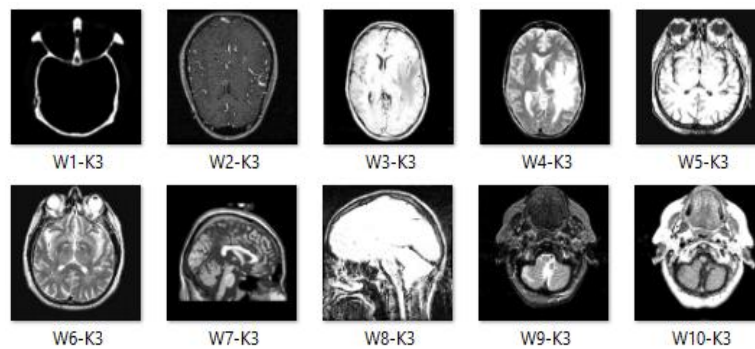

Figure 7: the results of the proposed Wiener-High Boost filter with using High Boost kernel (K1)
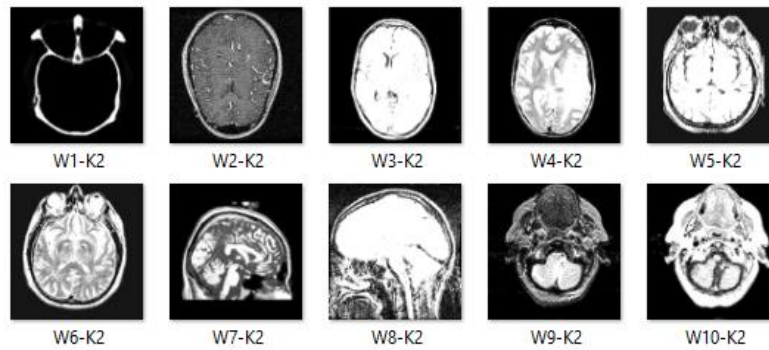
Figure 8: the results of the proposed Wiener-High Boost filter with using High Boost kernel (K2)

Figure 9: the results of the proposed Wiener-High Boost filter with using High Boost kernel (K3).

From Figure 6 to Figure 8, the proposed filter (Wiener-High Boost) shows the human visual system the clarity in the edge information compared with the traditional Wiener filter and the Blind image deconvolution technique, as shown in Figure 5 and Figure 6, respectively. The following tables from Table 1 to Table 4 show the numerical results of the proposed algorithm with three types of High-Boost kernels.

Table 1: Performance comparison of the Blind image deconvolution, the traditional Wiener, and the proposed filter using Wiener filter and High Boost filter using the image Contrast metric.

Method Images Imag	B-ID	T-WF	Proposed-K1	Proposed-K2	Proposed-K3
Imge1	13.6949	19.8716	27.2145	**32.3472**	19.2009
Imge2	20.0403	24.5716	44.9372	**61.9807**	23.4725
Imge3	26.9954	37.8634	**49.3775**	46.0955	36.7278
Imge4	22.2847	33.4760	48.7473	**51.8717**	32.1893
Imge5	37.3467	52.8208	65.5873	**66.3413**	50.9441
Imge6	26.7847	39.7928	61.9788	**66.5127**	37.9610
Imge7	17.3406	27.2254	47.4915	**58.6982**	37.9610
Imge8	51.3740	72.6968	81.8917	**92.2449**	70.4274
Imge9	19.1791	25.8488	46.6282	**62.0497**	24.6495
Imge10	31.3799	43.3024	**63.1723**	60.2018	41.9098

Table 2: Performance comparison of the Blind image deconvolution, the traditional Wiener, and the proposed filter using Wiener filter and High Boost filter using the Gradient Energy metric.

Method Images I	B-ID	T-WF	Proposed-K1	Proposed-K2	Proposed-K3
Imge1	16.8627	21.7038	24.7657	**27.3729**	21.3555
Imge2	29.4156	37.2054	62.3400	**78.6264**	35.5308
Imge3	34.6723	41.9862	**45.5381**	32.0834	40.9371
Imge4	34.5116	48.8177	**56.9161**	52.7232	47.8314
Imge5	56.5197	**69.9015**	61.8710	53.3748	68.8414
Imge6	44.2279	59.7649	**72.3376**	68.2472	58.1955
Imge7	29.8559	45.3462	63.2071	**64.8014**	58.1955
Imge8	79.0751	**99.2355**	80.9379	79.7306	98.2118
Imge9	32.7586	44.0291	65.5877	**72.6691**	42.2007
Imge10	48.7037	60.9486	**63.1723**	55.8673	60.1102

Table 3: Performance comparison of the Blind image deconvolution, the traditional Wiener, and the proposed filter using Wiener filter and High Boost filter using the Histogram Entropy metric.

Method Images	B-ID	T-WF	Proposed-K1	Proposed-K2	Proposed-K3
Imge1	2.0265	2.9622	3.3064	**3.5340**	2.9314
Imge2	5.5449	5.8021	6.6615	**7.0935**	5.7386
Imge3	4.5878	**5.4786**	5.1895	4.1151	5.4418
Imge4	4.5937	5.3921	**5.5077**	5.2592	5.3555
Imge5	6.3393	**6.3748**	5.8321	5.3465	6.3232
Imge6	5.7501	6.0271	**6.4380**	6.1672	5.8509
Imge7	4.5050	5.0134	5.5309	5.4627	**5.8509**
Imge8	**7.7056**	7.6758	6.0248	5.5888	7.6831
Imge9	4.6871	5.1269	5.8376	**6.0814**	5.0726
Imge10	5.2806	**5.8211**	5.1198	5.2414	5.7984

Table 4: Performance comparison of the Blind image transformation, the traditional Wiener, and the proposed filter using Wiener filter and High Boost filter using the Spatial Frequency metric.

Method Images	B-ID	T-WF	Proposed-K1	Proposed-K2	Proposed-K3
Imge1	1.3448	1.7150	1.9499	**2.1359**	1.6886
Imge2	3.2132	3.6202	5.2387	**6.2058**	3.5085
Imge3	2.9300	3.4489	**3.5210**	2.4170	3.3830
Imge4	2.9045	3.7944	**4.1303**	3.8136	3.7414
Imge5	4.5005	**5.1770**	4.4846	3.9283	5.1261
Imge6	3.7698	4.5878	**5.2434**	4.9389	4.4916
Imge7	2.7274	3.6356	4.5717	**4.5888**	4.4916
Imge8	6.3539	**7.3707**	5.7884	5.5738	7.3338
Imge9	3.0004	3.6556	4.8222	**5.1865**	3.5535
Imge10	3.8586	**4.5566**	4.3943	4.0305	4.5193

The Tables from 1 to T 4, show the performance comparison of the Blind image transformation (B-ID), the traditional Wiener filter (T-WF), and the proposed filter (Proposed-K1, Proposed-K2, and Proposed-K3). The Spatial Frequency metrics, which are: image contrast, Gradient Energy, Histogram Entropy, and Spatial Frequency, were used for this purpose. The best values of these metrics are shown in bold.

From the results above, we can notice that the proposed filter based on the Wiener filter and High Boost filter using kernel K2 with the value of A equal to 3 compared with traditional filters, produced good results, especially in terms of contrast values. The proposed filter in terms of the Gradient Energy and the Histogram Entropy values also produced good results when using the kernel K1 with the A value equal to 2. When the value of A is equal to 1, the proposed method improves the quality of the image by an amount approximately equal to the amount of improvement of images using the standard Wiener filter. In addition, the proposed filter solves the problem of darkness in the input image. For example, the image, imge2, is improved better by using the proposed filter. This means that the proposed method is useful for improving the sharpness of images that suffer from darkness. For a value of A > 3, the resulting image will be highly luminous due to an increase in high frequencies, which leads to masking the low frequencies that contain important details in the image.

6. Conclusion

Medical images with high contrast and good focus take advantage of the characteristics of the images and give better-quality images that help in reaching a more accurate medical diagnosis. Some studies have confirmed that the traditional Wiener filter is unable to rebuild high-frequency components such as edges and texture. In this work, the proposed filter combines the Wiener filter and the High Boost filtering. The performance of the proposed filter was evaluated by using four types of sharpening metrics, which are image Contrast, Gradient Energy and Histogram Entropy. Depending on the results that have been reached, the fluctuations in image quality in terms of removing noise, blur, and increasing sharpening using the methods mentioned in this paper are in the following descending order: The proposed filtering uses the combination of Wiener and High Boost filters, the Standard Wiener filter, and

Blind image deconvolution. As a final result, the proposed filter is useful for darkening medical images. It gives them more clarity while removing noise from them.

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