OPG Images Denoising Using Hybrid filtration Approach

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Abstract: All medical images are suffering from some kind of noise. Low contrast, blurring, and poor quality are vital problems that appear in the production of medical images. OPG (orthopantomography) images are also suffering from the same above problems; so that many types of filtration techniques have been proposed to overcome with these drawbacks because noise can affect the quality and validation of diseases diagnosis. This paper proposes a hybrid method of noise filtration for OPG images based on adaptive median filter and discrete wavelet transform. The analysis of simulation results show that the proposed method produces more desirable results for mixed noise denoising which contains Salt & Pepper, Gaussian, and Speckle noise compared with three denoising approaches which are standard median filter, adaptive median filter, and discrete wavelet transform. The proposed method achieves averaged PSNR of 31.38 dB and averaged SSIM of 0.9042 for mixed noise.

Keywords: Image denoising, OPG image, Adaptive median filter, Discrete wavelet transform.

I. General Introduction

One of the major issues related to the medical images is that most of the images are suffered from noise and other different quality-related problems and difficulties in extracting suitable information. Therefore it necessary to design some techniques that can enhance the image in such a way so that, it will be suitable for further processing.

Improvement of the quality of images has always been one of the major tasks of medical image processing. In modern terms, improvements in sensitivity, resolution and noise reduction have equated higher quality with greater informational throughput [1-3].

Developing suitable and effective image enhancement techniques are of major interests of many researchers. It also helps physicians to easily interpret an image. Now, the enhancement can be of different types and the choice is dependent on the image as well as on the application [1].

In order to mitigate some of the problems identified above, S. Arivazhagan et al; analyzed the performance of an Image Denoising System for Speckle noise using Discrete Wavelet Transform (DWT) for four levels of DWT decomposition [4]. While Ning Chun-yu et al; make a comparison between the traditional median filter and an adaptive median filter for denoising images affected by salt-and-pepper noise, they also studied the influence of the filter window size and the spatial density of noise on the quality of denoised image [5]. Ajay Boyat and Brijendra Kumar Joshi; Presented a denoising algorithm based on combined effect of wavelet transform and median filtering for Gaussian noise reduction [6]. Arpita Joshi et al; Introduced a joint scheme of Wavelet Transform using iterative noise density and Median Filtering to remove Salt and Pepper Noise [7]. Finally, Muhammad A. Asim et al; Presented a comparative study of different denoising techniques for the removal of poison noise from X-Rays images [8].

This paper proposed a powerful hybrid filtration scheme which combines adaptive median filter and discrete wavelet transform for OPG image denoising in order to obtain a suitable OPG image for diseases diagnosis. The noise removing results is presented for verifying the effectiveness of the new method against mixed noise (Sault-and-pepper noise, Gaussian noise, and speckle noise).

The remainder of the paper is organized as follows: Section 2 is devoted to the types of noise. Section 3 describes the filters that used in proposed scheme. Section 4 explains and describes the framework of the proposal method. Section 5 describes the results and makes a comparison between different noise removal filters and the proposed method. Section 6 comprises of conclusion and future work.

II. Types of noise

Image denoising performs a vital role in a wide variety of applications such as image registration, image segmentation, and image classification and visual tracking. The image may also get degraded by noise from any source at some stage acquisition or transferring through any media that is image may get corrupted from intrinsic or extrinsic source. Therefore, various types of noises are introduced to images during various processes as noted. Various types of noise have their own characteristics and are inherent in images in different ways. The most known types of noise models are [9] [10].

- Gaussian Noise Model: Gaussian noise is as a product of natural sources along with thermal vibration of atoms and discrete nature of radiation of warm objects.

- Impulse Valued Noise (Salt and Pepper Noise): In this form of noise some pixel values are modified within the image. Image pixel values are changed by corrupted pixel values either most or minimal pixel value that is why it is known as Impulse valued noise. It is specifically caused by malfunctioning of pixel elements in camera sensors, faulty memory space in storage, mistakes in digitization process and many more.

- Speckle Noise: This noise is multiplicative noise. There are located incoherent imaging systems such as the laser, radar and acoustics and so on; its probability density feature follows gamma distribution function.

III. Filtration Techniques

A. *Median Filter:*

The median filter (MF) is the best regarded non-linear ordered statistic digital filtering technique which is used to reduce noise in an image, as its name known, replaces the value of the corresponding pixel with the aid of the median of the gray levels inside the neighborhood of that pixel within the window.

Let $\mathbf{S_{xy}}$ is considered as a sub-image of the input noisy image, ***g(s,t)***. It's far targeted at coordinates ***(x,y).*** The function ***f(x,y)*** denotes the filter reaction at those coordinates. As a result, the equation of median filter is given by [5]: -

$$f(x,y) = \underset{(s,t)\in S_{xy}}{\text{median}}\{g(s,t)\} \qquad \text{..........} (1)$$

It should be stated that MF, is performed using a mask containing an ordinary number of pixels. If the neighborhood pixels under consideration consist of an even number of pixels, the median value of the two middle pixel values is selected as the output. The median pixel is calculated by first sorting all the pixel values inside the mask from the surrounding neighborhood pixels into numerical order and then replacing the pixel value being taken into consideration with the middle pixel value [5] [11].

For salt and pepper noise, the noisy pixels take only either the maximum or the minimum probable pixel value, for this reason, the median filter which having the assets of eliminating the extreme value, offers a good filtration of the noise [12].

MF has the capability of great noise reduction with considerably less blurring than linear smoothing filters of similar size [11].

B. The *Adaptive* Median Filter

The adaptive median filter (AMF) is a nonlinear ordered statistic filter that can handle impulse noise more effectively than the median filter. The MF can perform well on condition that the spatial density of the impulse noise is not large [11].

Both AMF and MF use a rectangular window. However, the difference is that the adaptive filter will regulate the size of the filter mask according to the size of the median of gray value. When the pixel in the center of the filter mask is ruled on to be noise, the value is substituted by means of the median; otherwise, the current pixel value is not changed.

AMF has a better advantage than MF is that it seeks out to preserve detail and high-frequency component while smoothing non-impulse noise. [13]

C. *Discrete Wavelet Transform*

Wavelets are functions mathematically representing scaled and shifted waveform copies of finite length called mother wavelet. The wavelet transform is used to analyze image into different frequency components at multiresolution scales [11].

The Discrete Wavelet Transform **(**DWT) is like to a hierarchical subbands system where the subbands are logarithmically spread out in frequency and decomposed into limited band parts that represent subbands decomposition and perfectly reconstructed [14]. Decomposition of the wavelet, signal breaks it into two classes; low pass and high pass. These classes individually carry information of original signal [7].

DWT decomposes the original image and transforms it into four-part which is normally labeled as LL, LH, HL, and HH as in the schematic illustrated in Figure 1-a. The LL subband can be advance decomposed into four subbands labeled as LL2, LH2, HL2, and HH2, as shown in Figure 1-b [14][15].

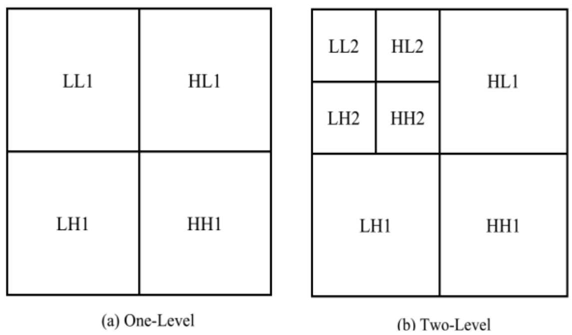
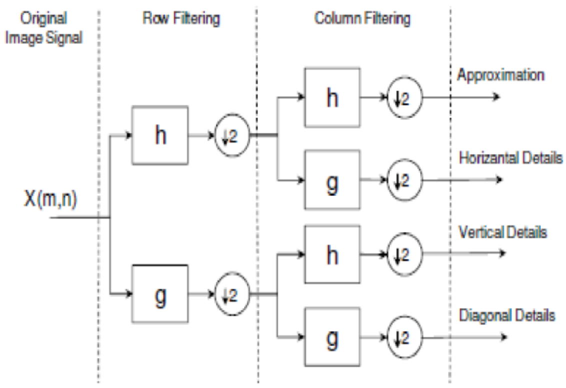
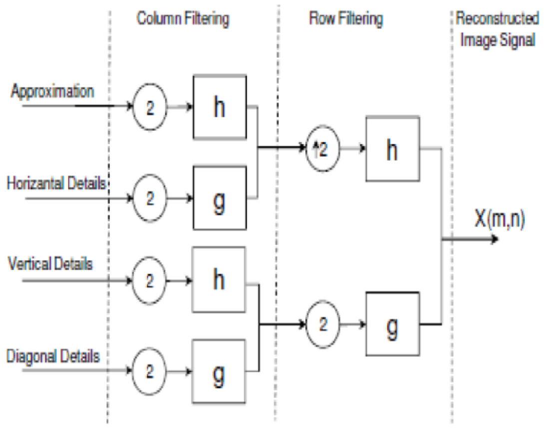


Figure (1) Discrete Wavelet Transform decomposition of image.

The LL part comes from low pass filtering in both directions and it is called the approximation which is the most like original picture. The remaining parts are called detailed components. The LH arises from low pass filtering in the vertical direction, HL comes from high pass filtering in the horizontal direction and HH represents the diagonals details. For a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency. Figure (2) below illustrate the DWT decomposition and reconstruction for level 2 steps of a 2D image signal [15]:



(a)



(b)

Figure (2) illustrates the DWT decomposition and reconstruction for level 2 for 2D image.

Wavelet Thresholding in the denoising process is based on that, the energy of the signal to be defined essences on some wavelet coefficients, despite the fact the energy of noise spreads throughout all wavelet coefficients [16].

The threshold enacts a significant role in the denoising method. A small threshold value will reserve the noisy coefficients even though large threshold value chiefs to the loss of coefficients that hold the details of the image. The purpose of the Wavelet threshold in denoising is to eliminate distributed Gaussian noise which is independent and identically properties. [14] [15].

Thresholding is one of the vital steps to noise reduction. The function of the thresholding is a wavelet shrinking function which determines how the threshold is implemented to wavelet coefficients. Thresholding is used to segment an image by setting all pixels whose intensity values are above a threshold to a foreground value and all the remaining pixels to a background value. Thresholding is essentially divided into two categories: hard Thresholding and soft Thresholding [16].

Hard thresholding is called keep or kills, keep the elements whose absolute value is greater than the threshold. Set the elements lower than the threshold to zero. While soft thresholding is called shrink or kill, which is an addition of hard thresholding. Initially, setting the elements whose absolute values are lower than the threshold to zero and then shrinking the other coefficients [14] [16].

Hard thresholding is more intuitively appealing and also it introduces artifacts in the recovered images. On the other hand, Soft thresholding is more efficient and it is used for the entire algorithm [12].

Soft thresholding is considered as a recognized thresholding rule. Owing to its effectiveness and simplicity and visually introduce more agreeable images [12] [13].

IV. Proposed Denoising Method

In this proposal, we try to provide a model that shows satisfactory responses to numerous types of noise that affects the OPG images. So we've used two efficient filters to remove that noise. The first one is Adaptive Median Filter which will be responsible for removing the salt-and-pepper noise very efficiently [5][11][12]. While we utilize Discrete Wavelet Transform for the purpose of disposal of other types of noise as a second stage [4][8], especially Gaussian noise [9].

By adopting this approach which offers a hybrid filtration for OPG images, which is abbreviated by HFOPG, we can later use these images for the purpose of diseases diagnosis, for example, tumor and cysts detection.

Figure (3) shows the flowchart of the proposed HFOPG, which consists of adaptive median filter followed by discrete wavelet transform for denoising images that suffering mixed noise effect.

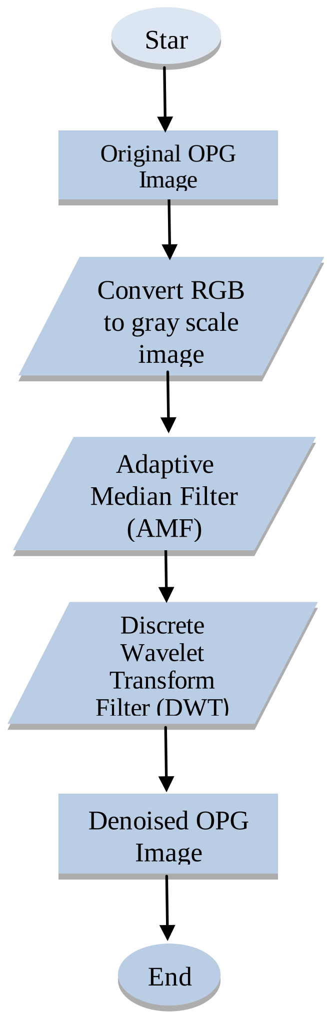


Figure (3) Flowchart of HFOPG

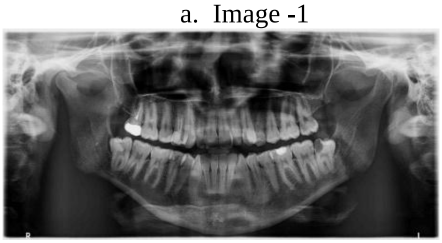
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 7, Issue 3, March 2018, ISSN: 2278 – 1323

V. Results and Discussion

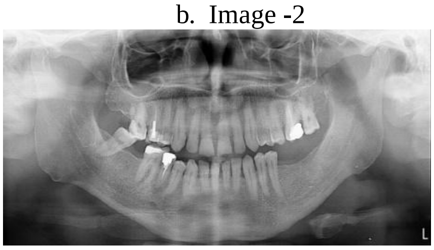
In this paper, three OPG X-ray images are used, as shown in Figure (4), in order to evaluate the performance of the denoising process. MF, AMF, and DWT are considered; also, two possible compounds of DWT followed by AMF and another approach presents AMF followed by DWT are used as a hybrid filtration technique. The proposed method is considered after evaluation the hybrid filtration technique by choosing the best performance compared with three filters individually.

The test is applied by adding three types of noise (Salt-and-pepper, Gaussian, and Speckle noise) to our sampled OPG images. Salt-and-pepper noise is added with probability (10%), (30%) and (50%) to the three images. Gaussian noise is added with variance (0.01), (0.05), and (0.1) with mean equal to zero. Speckle noise is added with variance (0.01), (0.05), and (0.1). Finally, mixed of these noises is added with noise variances 10% for salt and pepper and (0.01) for Gaussian and speckle noise respectively. Each of the obtained result is compared with the proposed method.

a. Image -1



b. Image -2



c. Image -3

Figure (4) Original OPG images without any denoising.

In order to make the comparison, two evaluation parameters are utilized, which are Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Matrix (SSIM).

PSNR compares the maximum power of the signal input image to the noise power that affects the fidelity of the image representation.

Define PSNR using the following equation:

$$PSNR = 10log_{10}\left(\frac{255^2}{D}\right) \quad \ldots\ldots (2)$$

Where,

$$D = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left(x_{m,n} - \hat{x}_{m,n}\right)^2 \quad \ldots\ldots\ldots\ldots (3)$$

Where, $x_{m,n}$ and $\hat{x}_{m,n}$ denotes as the gray values of the pixel at coordinates (m,n) before and after the denoising process.

SSIM is valuable for anticipating the perceived quality of the image [5] [8]. It is utilized for determining the similarity between two images X and Y and calculated as shown [18]:

$$\mathrm{SSIM}(X,Y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad \ldots\ldots\ldots\ldots (4)$$

With μ_x the average of x; μ_y the average of y; $\sigma^2_x$the variance of x; σ^2_y the variance of y; σ_{xy} the covariance of x and y; c1and c2 are constants.

Firstly, the images tested with salt and pepper noise. Table1 and Table2 illustrate PSNR and SSIM values of the three images denoised by different methods. The proposed method almost achieves the best results. However, the results of the adaptive median filter are so close to HFOPG results.

Table 1. PSNR (dB) of the denoised images with salt-and pepper noise.

Images	Noise variance	MF	AMF	DWT	DWT_AMF	HFOPG
1	0.1	44.23	**47.93**	32.67	37.81	47.86
	0.3	40.86	44.91	29.47	35.65	**45.12**
	0.5	35.79	37.82	29.36	32.53	**37.89**
2	0.1	44.77	**47.82**	32.55	36.83	47.73
	0.3	40.64	43.64	29.34	33.75	**43.75**
	0.5	35.38	37.88	29.30	32.22	**37.92**
3	0.1	49.45	53.56	32.22	42.19	**53.73**
	0.3	43.02	43.62	29.50	36.06	**43.71**
	0.5	36.62	39.69	27.74	34.35	**39.75**

The OPG images are tested again with Gaussian noise. Table 3 and Table 4 show the PSNR and SSIM of the denoised images. The hybrid filtration gives better result comparing with individual filters. Moreover, the proposed method achieves the higher values of PSNR and SSIM in more than half cases.

Table 2. SSIM of the denoised images with salt-and pepper noise.

Images	Noise variance	MF	AMF	DWT	DWT_AMF	HFOPG
1	0.1	0.9744	0.9873	0.6158	0.9181	0.9863
	0.3	0.9158	0.9758	0.5968	0.7520	0.9788
	0.5	0.7521	0.8680	0.5852	0.6220	0.9182
2	0.1	0.9752	0.9881	0.6130	0.8997	0.9872
	0.3	0.9488	0.9688	0.5323	0.6890	0.9526
	0.5	0.6263	0.7263	0.5310	0.6137	0.6133
3	0.1	0.9915	0.9921	0.6390	0.9612	0.9915
	0.3	0.9562	0.9570	0.4846	0.7306	0.9592
	0.5	0.7530	0.9132	0.3226	0.5820	0.9117

Table 3. PSNR (dB) of the denoised images with Gaussian noise.

Images	Noise variance	MF	AMF	DWT	DWT_AMF	HFOPG
1	0.01	32.11	32.68	31.93	33.78	**33.93**
	0.05	29.40	29.56	29.66	30.22	**30.64**
	0.1	28.84	28.89	29.08	**30.02**	29.92
2	0.01	31.68	31.93	30.76	32.82	32.86
	0.05	29.10	29.47	29.23	**30.73**	30.45
	0.1	28.50	28.58	29.05	**29.12**	28.98
3	0.01	31.24	31.86	31.52	32.82	**32.96**
	0.05	29.09	29.34	28.65	30.58	**30.69**
	0.1	28.49	28.57	28.26	29.51	**29.55**

Table 4. SSIM of the denoised images with Gaussian noise.

Images	Noise variance	MF	AMF	DWT	DWT_AMF	HFOPG
1	0.01	0.8264	0.8266	0.8059	0.8116	0.8211
	0.05	0.5635	0.5659	0.5689	0.6419	0.6551
	0.1	0.4236	0.4245	0.4384	0.6435	0.5692
2	0.01	0.8858	0.8869	0.8745	0.8961	0.8985
	0.05	0.6493	0.6482	0.6470	0.6684	0.6634
	0.1	0.5230	0.5233	0.5370	0.5441	0.5432
3	0.01	0.8693	0.8722	0.8870	0.8961	0.8962
	0.05	0.6622	0.6688	0.6509	0.6649	0.6687
	0.1	0.5432	0.5475	0.5422	0.5422	0.5445

Table 5. PSNR (dB) of the denoised images with Speckle noise.

Images	Noise variance	MF	AMF	DWT	DWT_AMF	HFOPG
1	0.01	36.24	35.78	34.61	36.56	**37.03**
	0.05	31.93	31.99	31.00	32.14	**32.34**
	0.1	30.69	30.79	30.08	30.83	**31.13**
2	0.01	35.94	35.62	34.26	35.56	**38.83**
	0.05	31.99	32.05	31.18	32.13	**32.76**
	0.1	30.80	30.93	30.25	30.84	**31.12**
3	0.01	36.24	36.96	32.79	37.32	**37.81**
	0.05	31.87	31.91	29.82	32.53	**32.83**
	0.1	30.66	30.81	29.06	30.78	**30.82**

Now, the comparison is made with speckle noise. The highest values of PSNR and SSIM are achieved by proposed method; all tested filters achieve lower values of PSNR and SSIM than the proposed method, as shown in Table (5) and Table (6) respectively.

Table 6. SSIM of the denoised images with Speckle noise.

Images	Noise variance	MF	AMF	DWT	DWT_AMF	HFOPG
1	0.01	0.9774	0.9723	0.9623	0.9781	0.9794
	0.05	0.8727	0.8730	0.8613	0.8745	0.8768
	0.1	0.7942	0.7954	0.7589	0.7690	0.7897
2	0.01	0.9782	0.9793	0.9575	0.9632	0.9855
	0.05	0.8720	0.9730	0.9652	0.8731	0.9336
	0.1	0.8612	0.8623	0.8532	0.8865	0.8885
3	0.01	0.9504	0.9545	0.9281	0.9653	0.9663
	0.05	0.8690	0.8695	0.8147	0.8787	0.8820
	0.1	0.7661	0.7690	0.6926	0.7688	0.7692

Finally, the images are tested with mixed noised. Table (7) and Table (8) illustrate PSNR and SSIM of the results for different denoising methods. The proposed method has the highest PSNR and SSIM for denoising the mixed noise comparing with the other methods. Figure (5) shows an example of the denoised results using image1 in case of adding the mixed noise.

Table 7. PSNR (dB) of the denoised images with mixed noise.

Images	MF	AMF	DWT	DWT_AMF	HFOPG
1	30.98	31.21	30.20	31.42	**31.74**
2	30.68	30.84	29.82	31.02	**31.45**
3	30.27	30.39	29.25	30.64	**30.96**
Average	**30.64**	**30.81**	**29.75**	**31.02**	**31.38**

Table 8. SSIM of the denoised images with mixed noise.

Images	MF	AMF	DWT	DWT_AMF	HFOPG
1	0.8826	0.8835	0.6431	0.8842	0.9140
2	0.8715	0.8763	0.6367	0.8812	0.9124
3	0.8650	0.8677	0.6231	0.8795	0.8862
Average	**0.8730**	**0.8758**	**0.6343**	**0.8816**	**0.9042**

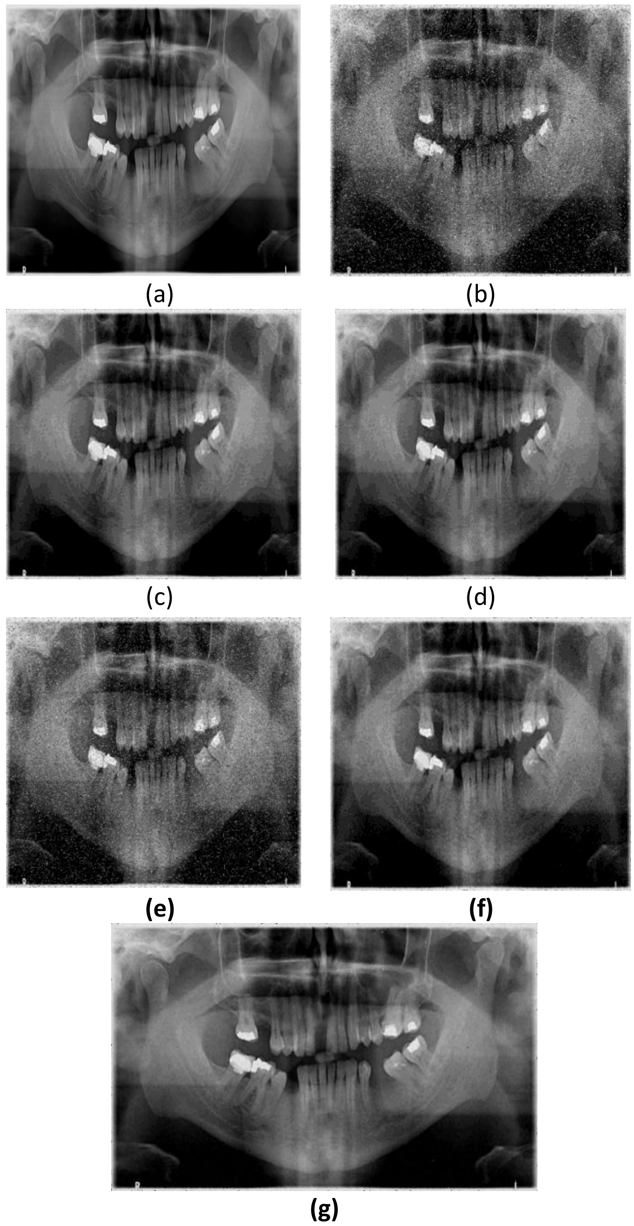


Figure 1. The denoised results.
(a) The original images. (b) The image with mixed noise. (c) Image denoised by median filter. (d) Image denoised by AMF filter. (e) Image denoised by DWT. (f) Image denoised by DWT_AMF. (g) Image denoised by HFOPG.

VI. Conclusion

This paper proposed a hybrid method of noise filtration based on adaptive median filter and discrete wavelet transform. The comparative evaluation of HFOPG has been done using three OPG images. The simulated results of image denoising for Salt & Pepper, Gaussian, and Speckle noise are shown. In order to consider a proper assessment, two performance parameters PSNR, SSIM have been used. The results confirmed that the proposed technique produced better results in comparison with MF, AMF, and DWT for reduction of mixed noise.

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