

A Case Study on Effects of Low Pass Filtering over Facial Image Processing and Proper Edge Detections

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ABSTRACT: The proper information extraction from a digitized photo of human face has a great necessity in today's research work. Different types of high frequency noises must be removed in order to get smooth and ideal information from the picture. The choice of correct low pass filter is important in order to remove significant amount of high frequency noise components without affecting the facial information in the image. A case study has been performed with several low pass filtering techniques in order to suggest the probable better filtering techniques for different types of noises in different circumstances. The variations of different filter performances alongside their dimensions are also addressed in this paper.

KEYWORDS: Low Pass Filter, Mean Filter, Median Filter, Wiener filter, Gaussian Noise, Salt and Pepper Noise, Poisson Noise.

I. INTRODUCTION

Information extraction from a digitized image of human face is one of the important applications in the recent digital image processing field. After acquiring a digitized image, several noises can attenuate the image and degrade its quality. Noise is a high frequency component to an image. The variation of its amplitude with respect to unit space is higher than the other pixels or regions of the image. A suitable low pass filter technique should be involved into this process in order to remove the noises without affecting or degrading the quality of the image. Degradation of the quality of the image involved loss of sharpness, removal of important edge or line information from the image while the filtering is in progress. Careful observation and choice of low pass filter with measured dimension is the key to achieve next to perfect reconstruction of the image free from noises. In this paper, case studies between different types of low pass filter with different dimension are examined for digitized human face images in order to suggest the better alternative for specific situations. Different types of noises are also addressed by this case study. Effects of these filtering over proper recovery of edges and lines in the image will also be monitored.

II. RELATED AND PREVIOUS WORK

In this case study process, the noises which will be addressed are 1) Gaussian Noise, 2) Salt and Pepper Noise, 3) Poisson Noise and 4) Speckle Noise.

Gaussian noise is a noise function with uniform power spectral density. The normal distribution is equal to probability density function [1]. It is normally generated by thermal vibration or high temperature radiation. Gray scale images normally get affected by this noise [4]. The case studies have been observed after the forceful inclusion of the Gaussian noise to the image. Salt and pepper noise or the impulse noise is a special type of noise with having pixels of high light intensity (white) and absolutely low light intensity (black). The maximum gray level of a gray scale image

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016

is normally accredited as ‘salt’ whereas the minimum gray level is accredited as ‘pepper’ [2][3]. This highly fluctuating intensity variation noise can be helpful to study the effects of different type of low pass filtering in the noise attenuated digitized image. This noise is generated due to imperfect analog to digital conversion of images [4]. Poisson noise or shot noise is generated due to variation of quantum photon while generating the image. This noise obeys the Poisson distribution [4][5]. Speckle noise is a noise with multiplicative nature and can be seen in laser and radar operations [4][5]. Application of filters with images attenuated by one of these pre-mentioned noises will be observed and the effects of the filter operations with the variations of filter dimensions will also be notified.

Low pass filtering in digital images perform image smoothing, blurring. The sharp colour variation in RGB colour image and sharp variation of gray level in gray images per unit space provides high frequency region in that image. After suitable application of low pass filter towards that image, the sharp variation of gray level become smooth and the high contrasting regions (edge, line or isolated points) become blurred. Low pass filter is also used for reducing the contrast of the images. Some low pass filters are used to remove isolated and unwanted points. It is the choice of particular filter for particular problem which is the key to get the better results. In order to inspect the performances of different low pass filters in different ambient conditions, three types of low pass filters are chosen for this case study, 1) Linear mean or averaging filter, 2) Median filter and 3) Adaptive filter.

1) Linear mean or averaging filter: This filter performs the average of the surrounding pixels and places the final result into the target pixel. The averaging process transforms a sharp variation of gray levels into a smooth and slow variation of gray levels. In Fig. 1(a), a low pass averaging filter mask with 3×3 dimension. A 7×7 sized gray image has been shown in Fig. 1(b). The gray pixel values vary from 0 (black) to 100 (white). It can be clearly understood that the image has sharp vertical edge. After the image is being scanned or convoluted with the low pass averaging filter mask and replace the average values to the image, the sharp variation (from gray value 10 to 80) has been reduces and the resultant image is shown in Fig. 1(c).

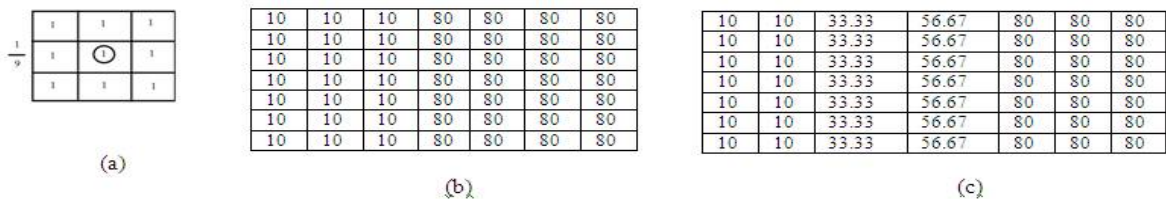


Fig. 1. (a) 3×3 mask mean filter (b) Gray image with sharp vertical edge (c) Gray image after smoothing by mean low pass filter.

2) Median filter: In this filter, median values of the gray level are used rather than mean or average value. The median of the neighbour pixels is the resultant gray level of the concerned pixel. Thus the final pixel value is free from extreme gray level variations due to some isolated pixels. This filter is thus used to remove isolated or spurious points from the system. Fig. 2(a) shows a 3×3 dimension median filter. Fig. 2(b) shows a 4×4 gray image with an isolated spurious point. That point is removed after scanning by the median filter and the result is shown in Fig. 2(c).

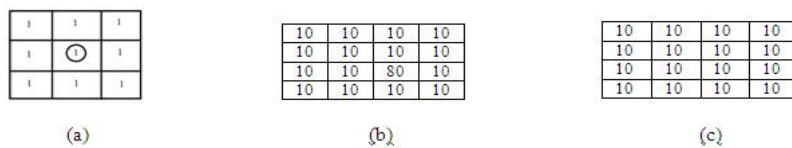


Fig. 2. (a) 3×3 mask median filter (b) Gray image with isolated spurious point (c) Gray image isolated point removal by median low pass filter.

3) Adaptive Filtering: This filtering is used to preserve valuable image information which may be lost while under operation in mean filtering. After successful mean filtering, all the edges are subjected to be smoothed or blurred by a certain limit. The edges, which are required to be present in the output image also, must be preserved (should not be 9

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016

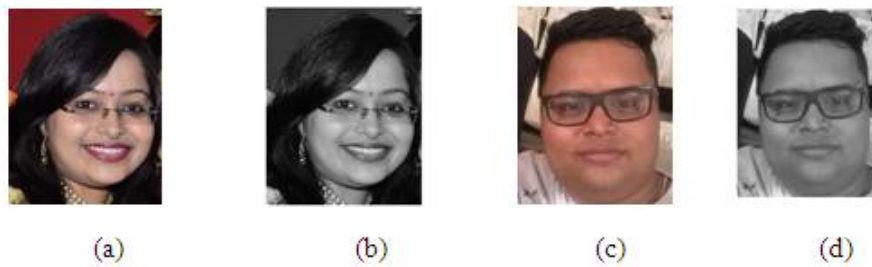


Fig. 3. (a) original RGB image1 (b) Gray version of image1 (c) original RGB image2 (d) Gray version of image2.

Next, these gray images are attenuated with zero mean 0.01 variance Gaussian noise. The resultant images are shown in Fig.4 (a) for image1 and 6(a) for image2. These noise attenuated images are then channelized through different type of noise reducing low pass filters. The effects for the respective images are shown in other figures of Fig. 4 and Fig. 6. The outcome images (for both image1 and image2) from 5×5 and 11×11 dimensioned filters are then transformed into edge detected image by suitable Sobel's edge detection operator. The respective Sobel's edge detected images are shown in Fig. 5 for image1 and Fig. 7 for image2.



Fig. 4. (a) Gaussian noise attenuated gray image1 (b) image1 after 5×5 mean filtering (c) image1 after 5×5 median filtering (d) image1 after 5×5 adaptive Wiener filtering (e) image1 after 11×11 adaptive Wiener filtering

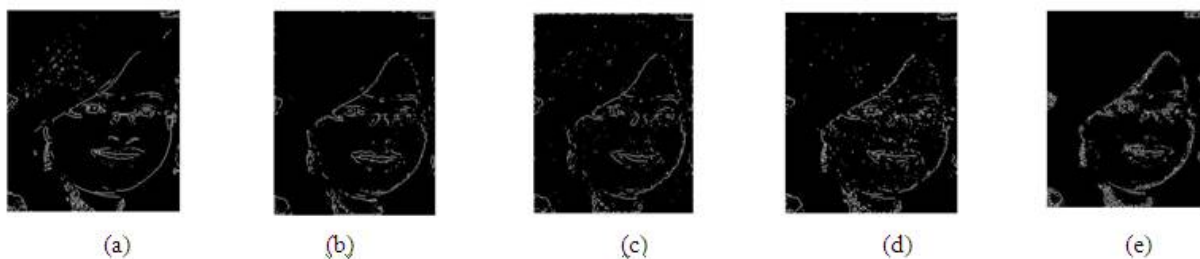


Fig. 5. (a) Edge detected image of Image1 before addition of Gaussian noise (b) Image after edge detection of 5×5 dimension mean filtered output from gray version of image1 (c) Image after edge detection of 5×5 dimension median filtered output from gray version of image1 (d) Image after edge detection of 5×5 dimension Wiener filtered output from gray version of image1 (e) Image after edge detection of 11×11 dimension Wiener filtered output from gray version of image1

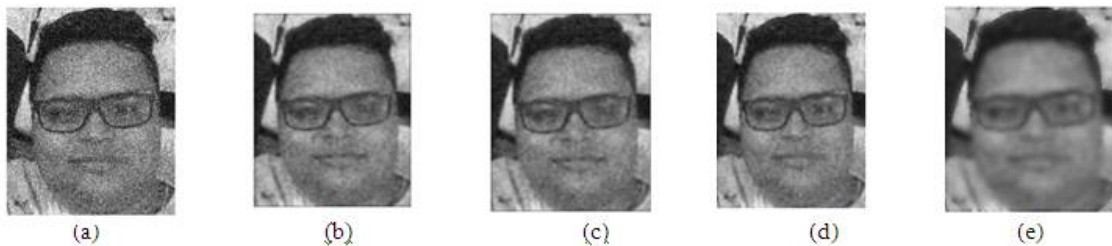


Fig. 6. (a) Gaussian noise attenuated gray image2 (b) image2 after 5x5 mean filtering (c) image2 after 5x5 median filtering (d) image2 after 5x5 adaptive Wiener filtering (e) image2 after 11x11 adaptive Wiener filtering



Fig. 7. (a) Edge detected image of Image2 before addition of Gaussian noise (b) Image after edge detection of 5x5 dimension mean filtered output from gray version of image2 (c) Image after edge detection of 5x5 dimension median filtered output from gray version of image2 (d) Image after edge detection of 5x5 dimension Wiener filtered output from gray version of image2 (e) Image after edge detection of 11x11 dimension Wiener filtered output from gray version of image2

From the comparisons, it can be observed that for same dimension filtering, mean filtering provides better noise reduction to the image. But mean filtering also adds additional blurring to the system which is its disadvantage. From these comparisons, it can be concluded that adaptive Wiener filtering provides the better noise reduction without blurring the image. The increment in dimension (from 5x5 to 11x11) for Wiener filtering causes additional blurring to the images. This blurring may help reducing further Gaussian noises but this causes loss of significant information of the images.

The effect of extra-blurring can be inspected in terms of edge detection. The high frequency edges in the images are always affected by the blurring or smoothing process. The edge detected original gray images are shown in Fig. 5(a) and Fig. 7(a) for image1 and image2 respectively. From the inspection of Fig. 5(b) and Fig. 7(b), it can be concluded that the original edges which do not belong to noise, are also removed by mean filtering in the process of noise reduction. The adaptive wiener filtering produces the better result in terms of noise reduction as well as protecting edge information of the images (Fig. 5(d) and Fig. 7(d)). But the increment in higher dimension (from 5x5 to 11x11) adds additional blurring to the system (Fig. 5(e) and Fig. 7(e)). This causes loss of image information.

III. EFFECTS OF DIFFERENT FILTERS TOWARDS SALT AND PEPPER NOISE

The same gray images obtained from image1 and image2 are used for the effects of different low pass filters and their suitable dimensions over different types of noise reductions. The gray image1 is attenuated by salt and pepper noise and then the noise reduction has been attempted by mean, median or adaptive wiener filter. The effects of the filters are shown in Fig. 8. The same operation is done for image2 and shown in Fig. 10. The edges after the filter application are inspected for image1 in Fig. 9 and that for image2 is shown at Fig. 11. The edges are inspected in order to find the appropriate filter for noise reduction for salt and pepper noise without distorting the images.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016



Fig. 8. (a) Salt and Pepper noise attenuated gray image1 (b) image1 after 5×5 mean filtering (c) image1 after 5×5 median filtering (d) image1 after 11×11 median filtering (e) image1 after 5×5 adaptive Wiener filtering



Fig. 9. (a) Edge detected image of Image1 before addition of Salt and Pepper noise (b) Image after edge detection of 5×5 dimension mean filtered output from gray version of image1 (c) Image after edge detection of 5×5 dimension median filtered output from gray version of image1 (d) Image after edge detection of 11×11 dimension median filtered output from gray version of image1 (e) Image after edge detection of 5×5 dimension Wiener filtered output from gray version of image1



Fig. 10. (a) Salt and Pepper noise attenuated gray image2 (b) image2 after 5×5 mean filtering (c) image2 after 5×5 median filtering (d) image2 after 11×11 median filtering (e) image2 after 5×5 adaptive Wiener filtering



Fig. 11. (a) Edge detected image of Image2 before addition of Salt and Pepper noise (b) Image2 after edge detection of 5×5 dimension mean filtered output (c) Image2 after edge detection of 5×5 dimension median filtered output (d) Image2 after edge detection of 11×11 dimension median filtered output (e) Image2 after edge detection of 5×5 dimension Wiener filtered output.

From Fig. 8, Fig. 9, Fig. 10 and Fig. 11, it can be shown that median filter works better in case of salt and pepper noise. Mean filter provides some amount of reduction towards salt and pepper noise but it also blurs the image. It can be

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016

demonstrated by Fig. 8(b) and Fig. 10(b). The necessary edge information is also lost after mean filtering. This can be shown by Fig. 9(b) and Fig. 11(b). From Fig. 8(e) and Fig. 10(e), it can be notified that adaptive Wiener filter provides least and inadequate filtering towards salt and pepper noise. From Fig. 8(c) and Fig. 10(c) it can be shown that median filter provides adequate and necessary filtering in order to remove salt and pepper noise. The reason why median filter works better in case of salt and pepper noise lies within the fact that salt and pepper noise adds extreme values of pixels in the image, either a pixel with extreme white or pixel with extreme black. The median filter always removes spurious and isolated points whose gray level differs a lot from the neighbour pixel points. Thus median filter works better in case of salt and pepper noise attenuated image. From Fig. 9(c) and Fig. 11(c) it can be summarized that median filter also preserves all the edge information. From Fig. 8(d) and Fig. 10(d), it can be shown that increasing dimension to the filter can add extra smoothing or blurring to the images. This will also remove necessary high frequency edge or line information (shown in Fig. 9(d) and Fig. 11(d)). Thus a proper dimensioned median filter can be an ideal solution towards salt and pepper noise in an image.

IV. EFFECTS OF DIFFERENT FILTERS TOWARDS POISSON NOISE

Gray images image1 and image2 will now be used to inspect effects of different low pass filters towards Poisson noise in an image. The noise is added to the images and the noise has also been reduced by different filters. The effects for image1 and image2 have been shown in Fig. 12 and Fig. 14 respectively. The Sobel's edge detected images are also tabulated in Fig. 13 and Fig. 15 respectively for image1 and image2 from the outputs of different filters.



Fig. 12. (a) Poisson noise attenuated gray image1 (b) image1 after 5×5 mean filtering (c) image1 after 5×5 median filtering (d) image1 after 5×5 adaptive Wiener filtering (e) image1 after 11×11 adaptive Wiener filtering



Fig. 13. (a) Edge detected image of Image1 before addition of Poisson noise (b) Image1 after edge detection of 5×5 dimension mean filtered output (c) Image1 after edge detection of 5×5 dimension median filtered output (d) Image1 after edge detection of 5×5 dimension Wiener filtered output (e) Image1 after edge detection of 11×11 dimension Wiener filtered output



Fig. 14. (a) Poisson noise attenuated gray image2 (b) image2 after 5×5 mean filtering (c) image2 after 5×5 median filtering (d) image2 after 5×5 adaptive Wiener filtering (e) image2 after 11×11 adaptive Wiener filtering



Fig. 15. (a) Edge detected image of Image2 before addition of Poisson noise (b) Image2 after edge detection of 5×5 dimension mean filtered output (c) Image2 after edge detection of 5×5 dimension median filtered output (d) Image2 after edge detection of 5×5 dimension Wiener filtered output (e) Image2 after edge detection of 11×11 dimension Wiener filtered output

From Fig. 12 and Fig. 14, it can be shown that the adaptive Wiener filter reproduces the original image better than the other filters (Fig. 12(d) and Fig. 14(d)). The output from 5×5 Wiener filter is much more prominent than the outputs of other filters with same dimension. Mean filter adds extra blurring to the system causing distortion towards the true edges and lines of the image (Fig. 12(b) and Fig. 14(b)). In case of Wiener filtering, increment of dimension also adds extra smoothing or blurring to the system which is disadvantageous towards faithful reproduction of original image from Poisson noise (Fig. 12(e) and Fig. 14(e)). After proper inspection of edge detected images from the outputs of different filters (Fig. 13 and Fig. 15), it has been justified that Wiener filter provides better filtering without adding too much blurring to the system for 5×5 masking (Fig. 13(d) and Fig. 15(d)). The true edges of the images have been lost after using the averaging filters (Fig. 13(b) and Fig. 15(b)). Edges can also be lost if the dimension of the filter gets increased (Fig. 13(e) and Fig. 15(e)).

V. EFFECTS OF DIFFERENT FILTERS TOWARDS SPECKLE NOISE

Gray versions of image1 and image2 have also been tested through Speckle noise and the effects of different low pass filters for noise reduction have been observed. The effects at the outputs from filters for image1 and image2 have been demonstrated in Fig. 16 and Fig. 18 respectively. The Sobel's edge detected images from the outputs of different filters for image1 and image2 are displayed in Fig. 17 and Fig. 19 respectively.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016



Fig. 16. (a) Speckle noise attenuated gray image1 (b) image1 after 5x5 mean filtering (c) image1 after 5x5 median filtering (d) image1 after 5x5 adaptive Wiener filtering (e) image1 after 11x11 adaptive Wiener filtering



Fig. 17. (a) Edge detected image of Image1 before addition of Speckle noise (b) Image1 after edge detection of 5x5 dimension mean filtered output (c) Image1 after edge detection of 5x5 dimension median filtered output (d) Image1 after edge detection of 5x5 dimension Wiener filtered output (e) Image1 after edge detection of 11x11 dimension Wiener filtered output

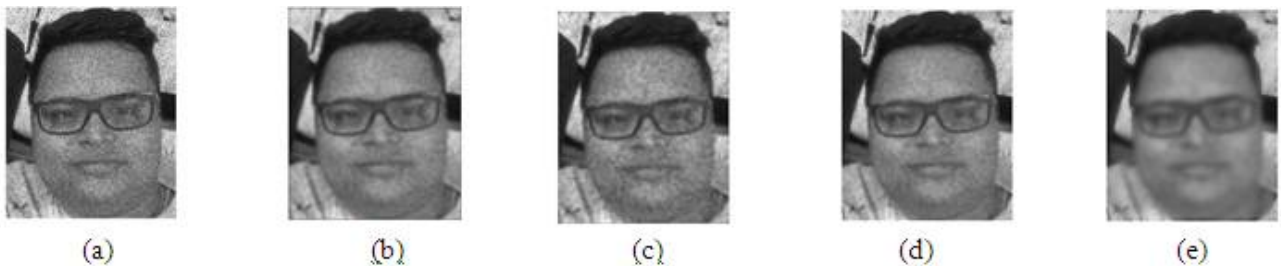


Fig. 18. (a) Speckle noise attenuated gray image2 (b) image2 after 5x5 mean filtering (c) image2 after 5x5 median filtering (d) image2 after 5x5 adaptive Wiener filtering (e) image2 after 11x11 adaptive Wiener filtering



Fig. 19. (a) Edge detected image of Image2 before addition of Speckle noise (b) Image2 after edge detection of 5x5 dimension mean filtered output (c) Image2 after edge detection of 5x5 dimension median filtered output (d) Image2 after edge detection of 5x5 dimension Wiener filtered output (e) Image2 after edge detection of 11x11 dimension Wiener filtered output

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 7, July 2016

From analysing Fig. 16 and Fig. 18 it can be observed that the noises are reduced better in mean filtering. But it adds extra smoothing or blurring to the images (Fig. 16(b) and Fig. 18(b)). The output of the Wiener filter is more prominent than the other filter as this filter adds less amount of blurring to the images (Fig. 16(d) and Fig. 18(d)). But if the dimensions are increased, this filter also adds blurring to the images. So a proper choice of dimension to the filter is important (Fig. 16(e) and Fig. 18(e)). After analysing the Sobel's edge detected images after filtering, this can also be demonstrated that mean filter removes maximum Speckle noise but adds smoothing which in turns, removes true edges of the images (Fig. 17(b) and Fig. 19(b)). Median and Wiener filter preserves true edges and lines at the output images (Fig. 17(c), Fig. 17(d), Fig. 19(c) and Fig. 19(d)). The addition in dimensions reduces sharpness of the images and true high frequency components like edges, lines may be lost at the output images from the filter (Fig. 17(e) and Fig. 19(e)).

VI. CONCLUSION

After processing through a set of case studies with different types of noises alongside different types and dimensioned filters, it has been observed that filter with proper type and dimension is essential towards successful noise reduction from the image without reducing the sharpness of the image. Mean filtering effectively reduces noises from the image but significantly added blurring to the image, causing reduction of image sharpness. Adaptive Wiener filter works better than the other filters tested in this paper for most cases with proper noise reduction and proper sharpness preservation. Median filter works better than the other filters analysed in this paper for Salt and Pepper noise. The increment of dimensions adds loss of true edges and lines and reduces sharpness of the image though it helps us reduce noise more than the lower dimensioned filters.

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