Periodic and Quasi Periodic Noises and their Removal using Various Filters: A Review

[1]Shashank Jain, [2]Amit Gupta
[1]Research Scholar, [2]Asst. Professor,
M. Tech., Communication Systems, GGITS, Jabalpur

Abstract: digital image processing is a major area of research due to the various applications based on images. In online and offline applications images are corrupted with various kind of noises, thus mechanisms are proposed to suppress the noises as they cannot be completely eliminated. The noises are suppressed using the various kinds of filters linear, non-linear and adaptive. However, with periodic and quasi-periodic noises a careful design of filter is desired, thus many algorithms designs are presented. This paper, presents the review of the some of the recently proposed mechanism with their advantages and disadvantages.

Keywords: Quasi Periodic Noise, Periodic Noise, Noise Removal.

1. INTRODUCTION

The field of digital image processing refers to the use of computer algorithms to extract useful information from digital images. The entire process of image processing may be divided into three major stages:

(i) *Image acquisition*: converting 3D visual information into 2D digital form suitable for processing, transmission and storage.

(ii) *Processing*: improving image quality by enhancement, restoration, etc.

(iii) *Analysis*: extracting image features; quantifying shapes and recognition [1-3].

In the first stage, input is normal image, and obtained output is digital image. In the second stage of processing, both input and output are digital images; however the output image is an improved version of the input. In the final stage, input is still a digital image which is further used in the feature extraction, but the output is description of the contents. Block diagram of the process shown in Figure 1.

Figure 1: Image Processing Steps

As information travel through any digital media, it may get corrupted with various kind of noise sources, thus restoration mechanism is desirable to error free input information. This paper explores periodic and quasi periodic noises, and recent methods are discussed to suppress these noises.

2. NOISES ANALYSIS

Noise is any undesirable signal. Noise is everywhere and thus we have to learn to live with it. Noise gets introduced into the data via any electrical system used for storage, transmission, and/or processing. In addition, nature will always plays a "noisy" trick or two with the data under observation. When encountering an image corrupted with noise you will want to improve its appearance for a specific application. The techniques applied are application-oriented. Also, the different procedures are related to the types of noise introduced to the image. Noise is undesired information that contaminates the image. In the image denoising process, information about the type of noise present in the original image plays a significant role.

In a general way, the form in which noise is present in an image is additive.

An additive noise follows the rule

$$C(a, b) = I(a, b) + N(a, b), \quad (1)$$

Where $I(a, b)$ is the original signal, $N(a, b)$ signifies the noise proposed into the signal to develop the corrupted image $C(a, b)$, and (a, b) stands for the pixel location.

2.1 Periodic Noise

This noise is generated from electronics interferences, especially in power signal during image acquisition. This noise has special characteristics like spatially dependent and sinusoidal in nature at multiples of specific frequency. It's appears in form of conjugate spots in frequency domain. It can be conveniently removed by using a narrow band reject filter or notch filter.

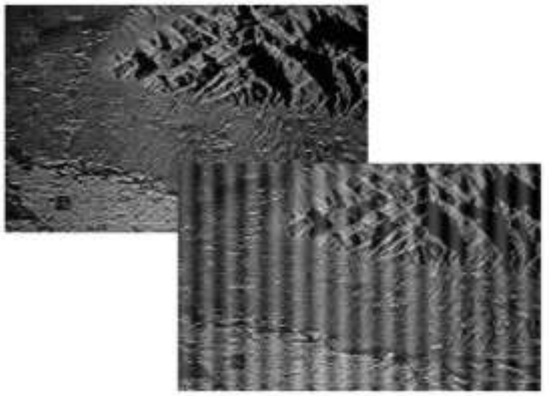


Figure 2 Periodic Noise

Periodic noise typically arises from interference during image acquisition. Spatially dependent noise type can be effectively reduced via frequency domain filtering Noise parameters can often be estimated by observing the Fourier spectrum of the image – Periodic noise tends to produce frequency spikes [4] as shown in figure (2).

Many applications of digital images processing require an estimation of the noise level that should be local in time and in frequency such that non-stationary and coloured noise can be dealt with. Noise level estimation is usually done by explicit detection of time segments that contain only noise, or explicit estimation of harmonically related spectral components [5].

3. NOISE REMOVAL FUNDAMENTALS

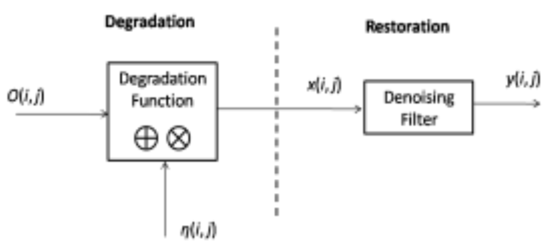


Figure 3 Image degradation and restoration process

In figure 3 image degradation and restoration process is shown. $O_{i,j}$ is an input object $\eta_{i,j}$ is degrading term (may include noise, blurring or both) so $x_{i,j}$ is

$$x_{i,j} = O_{i,j} + \eta_{i,j} \qquad (2)$$

or

$$x_{i,j} = O_{i,j} \times \eta_{i,j} \qquad (3)$$

$$y_{i,j} = H\left[x_{i,j}\right] \qquad (4)$$

H is filter operator.

Let us consider that the degradation is represented by an operator A. Then the equation 2, 3 can be written as

$x_{i,j} = A\left[O_{i,j}\right]$, now simply using basic concept of matrix, equation can be converted into

$A^{-1}\left[x_{i,j}\right] = A^{-1}A\left[O_{i,j}\right] = \left[\hat{O}_{i,j}\right]$ where, cap denotes the expected value. In most of the image processing problems A^{-1} is singular. Therefore, estimation of $\hat{O}_{i,j}$ is not possible through inverse process. Therefore filtering based techniques are proposed to reduce noises or degradation (cannot eliminate).

3.1 FILTERS

In past, various techniques have been proposed for image filtering. Linear filtering techniques have been the most preferred methods over the years.

$$y(t) = \int_{-\infty}^{\infty} x(\tau)h(t-\tau)d\tau \qquad (5)$$

Where $x(t)$ is input image, $h(t)$ is filter impulse function and $y(t)$ is the output image.

Most of the techniques developed assume a Gaussian noise model for the statistical characteristics of the underlying process, and thus parameters of a system are optimized optimally. Old image filtering techniques basically rely on transform domain filtering and contrast enhancement, and most of them are linear [6-8].

Although, in the image processing, it has been proved that the linear techniques are not effective as they are not able to cope with the nonlinearities of the image formation model and don't make into note of visual system of humans. These techniques, hence, frequently create blurred images and are not sensitive to impulse noise. Image signals have the composition of flat regional parts and unexpectedly changing areas like edges, which convey essential information for visual perception. Therefore, in the course of the last 15 years, nonlinear methods have been observed to be more impressive for this task. Nonlinear methods can suppress non-Gaussian and signal dependent noise in order to preserve crucial signal elements, for example, edges and fine details and discard degradations happening at the time of signal formation or transmission through nonlinear channels [9].

Filters having decent characteristics of edge and image detail preservation are very much appropriate for image filtering and improvement. New techniques and algorithms, which can make use of the rise in computing power and can deal with more realistic suppositions, are required. Therefore, the advancement of nonlinear filtering procedures, which works equally fine under wide variety of applications, is of very high significance.

Filtering techniques in the frequency domain are based on modifying the Fourier transform to achieve a specific objective and then computing the inverse DFT to get information back to the spatial domain [1, 0]. If *b* is an image, then its Fourier transform will reflect the frequencies of the periodic parts of the image. By masking or filtering out the unwanted frequencies one can obtained a new image by applying the inverse Fourier transformation. A filter is a matrix with the same dimension as the Fourier transform of the padded image. The components of the filter usually vary from 0 to 1. If the component is 1, then the frequency is allowed to pass; if the component is 0, then the frequency is tossed out.
The form of the filter function determines the effects of the operator. There are basically three different kinds of filters: low pass, high pass and band pass filters.
A low-pass filter attenuates high frequencies and retains low frequencies unchanged. The result in the spatial domain is equivalent to that of a smoothing filter; as the blocked high frequencies correspond to sharp intensity changes, i.e.to the fine-scale details and noise in the spatial domain image. A high pass filter, on the other hand, yields edge enhancement or edge detection in the spatial domain, because edges contain many high frequencies. Areas of rather constant gray level consist of mainly low frequencies and are therefore suppressed [11].
A band pass attenuates very low and very high frequencies, but retains a middle range band of frequencies. Band pass filtering can be used to enhance edges (suppressing low frequencies) while reducing the noise at the same time (attenuating high frequencies).
Moreover, transform domain techniques are capable of removing some part of the noises. That is why in image enhancement DFT or FFT is used.
A 2-D low pass filter in the frequency domain means zeroing all frequency components above a cutoff frequency. The ideal filter can be represented by the circle with radius R_0

$$H(u,v)=\begin{cases}1, \text{ if } R \le R_0 \\ 0, \text{if } R > R_0\end{cases} \quad (6)$$

Where R_0 is cutoff frequency. This equation can be rewritten in terms of polar coordinate system:

$$H(u,v)=\begin{cases}1, \text{ if } u = R\cos\phi, v = R\sin\phi, \phi\in\{0,2\pi\}, R\in\{0,R_0\} \\ 0, \text{ otherwise}\end{cases} \quad (7)$$

Equation 6-7 represents an ideal low pass filter; all frequencies inside a circle radius R_0 are passed without change, but all frequencies outside the circle fully suppressed by the filter.
A 2-D ideal high pass filter is defined as:

$$H(u,v)=\begin{cases}0, \text{ if } R \le R_0 \\ 1, \text{if } R > R_0\end{cases} \quad (8)$$

Where R_0 is cutoff frequency. This equation can be rewritten in terms of polar coordinate system:

$$H(u,v)=\begin{cases}0, \text{ if } u = R\cos\phi, v = R\sin\phi, \phi\in\{0,2\pi\}, R\in\{0,R_0\} \\ 1, \text{ otherwise}\end{cases} \quad (9)$$

Band pass filter has two cut off frequencies R_1 and R_2 allow passing a frequencies within a band from R_1 to R_2. Equation 10 represents the ideal bandpass filter:

$$H(u,v)=\begin{cases}1, \text{ if } u = R\cos\phi, v = R\sin\phi, \phi\in\{0,2\pi\}, R\in\{R_1,R_2\} \\ 0, \text{ otherwise}\end{cases} \quad (10)$$

Unlike ban pass, band stop (band reject) filter allow to pass a frequencies within a band from zero to R_1 and from R_2 to infinite, the band $R_1 \ldots R_2$ in this case suppressed by a filter function. Equation 11 represents the ideal band stop filter:

$$H(u,v)=\begin{cases}1, \text{ if } u = R\cos\phi, v = R\sin\phi, \phi\in\{0,2\pi\}, R\notin\{R_1,R_2\} \\ 0, \text{ otherwise}\end{cases} \quad (11)$$

Notch filter are the most useful of the selective filters. A notch filter rejects or passes frequencies in predefined regions. The notch reject filters are constructed as products of high pass filters.

4. NOTABLE WORKS

4.1 Ashraf Abdel-Karim Helal Abu-Ein [2014]

In [12] an efficient methodology to remove periodic noise from digital images is proposed. The methodology steps is discussed, analyzed and implemented. Color image is to be converted to gray image, and then 2D fast Fourier transform (2DFFT) is to be applied on the gray image. The magnitude of applying 2DFFT is to be analyzed in order to get the periodic filter, which is to be correlated with the magnitude matrix, and the output of correlation is to be used with the angle matrix to get the de-noised gray image.

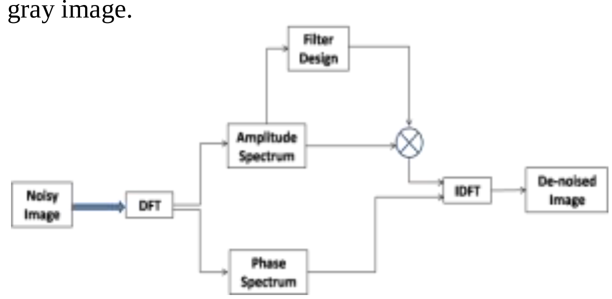


Figure 4 Methodology for periodic noise removal process

Methodology for periodic noise removal

The proposed methodology consists of the following sequence of steps:

Step1: Acquire the color image, apply direct conversion to convert color image to gray image and save the red and green components to be used later on in indirect conversion.

Step2: Transfer the gray image representation from time domain to frequency domain by applying 2D FFT which gives us the magnitude and angle matrix of the image, save the angle matrix to be used later on.

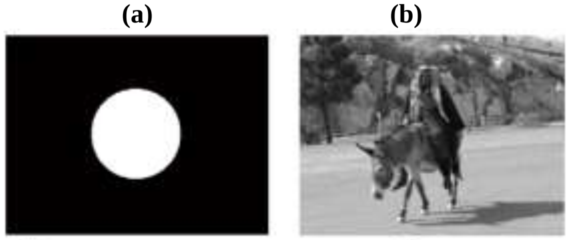
Step3: Analyze the magnitude matrix spectrum and prepare the filter mask.

Step 4: Correlate the magnitude matrix with filter mask.

Step 5: Use the correlated matrix and angle matrix and apply inverse FFT to get the new gray image.

Step 6: Apply inverse conversion to get the cleared color image.

(a) **(b)**



(c) **(d)**

Figure 5: (a) Input image, (b) the spectrum of input image, (c) the ideal low pass filter, (d) result of filtration process in spatial domain

The results of the above process are shown in figure 5. The original image is shown in figure 5(a). The spectrum of the input image is shown in figure 5(b). The ideal LPF is shown in figure 5(c). In the figure 5(d) recovered image is shown. In the above method ringing effect can be seen in the final image.

4.2Mandeep Kaur et.al., [2015] [13]

In this paper [13] a 2-D FFT removal algorithm for reducing the periodic noise in natural and strain images is proposed. For the periodic pattern of the artifacts, we apply the 2-D FFT on the strain and natural images to extract and remove the peaks which are corresponding to periodic noise in the frequency domain. Further the mean filter applied to get more effective results. The performance of the proposed method is tested on both natural and strain images. In this work two set of algorithms are presented.

Algorithms 1: Peak detection in the frequency domain.

1. Define a detection route such that the detected peaks are stored in an ascending order in terms of the distance to the origin (where the origin is the centre of the spectrum domain). Note that if only processes in the right half space of the centre because of the symmetry of the peaks (impulses) in the spectrum domain.
2. Define a local window of the size X*Y (where X and Y are odd) and find the maximum from the window pixels.
3. If the current pixel is just the same as the local maximum and also it is above a given threshold, it will be a new detected peak.

Algorithm2: Noise Removal Algorithm

1. Take a 2-D FFT to the processing image.
2. Use Algorithm 1 for local peaks detection in the frequency domain.
3. Compute the direction groups and define the set of deleted impulses.
4. Remove the selected impulses by using Algorithm 1, and then take the inverse 2-D FFT.
5. Apply the mean filter to suppress the peaks.
6. Apply the inverse 2D FFT for the spatial domain.

Normalize the updated pixels to obtain the same mean as the old.

(a) **(b)**

(c) **(d)**

Figure 6: (a) Original image (b) noisy image (c) filtered by mean filter (d) filtered by proposed method

The results of the process is shown in figure 6. In figure 6(a) original image is shown, in figure 6(b) noiy image corrupted with periodic noise is shown.in figure 6(c) filtered image by mean filter is shown, and filtered image with kaur method is shown in figure 6(d). It s clear from the figure that, noise is dimnished, however it is still visible in the image.

4.3 An A-Contrario Approach To Quasi-Periodic Noise Removal Fedric Sur [14][2015]

Images can be affected by quasi-periodic noise [14]. This undesirable feature manifests itself by spurious repetitive patterns covering the whole image, well localized in the Fourier domain.

While notch filtering permits to get rid of this phenomenon, this however requires to first detect the resulting Fourier spikes, and, in particular, to discriminate between noise spikes and spectrum patterns caused by spatially localized textures or repetitive structures. This work proposes a statistical a-contrario detection of noise spikes in the Fourier domain.

ALGORITHM

Spectral density is critical in evaluating quasi noise. This theory of detection is based on the thought that characters of interest (called *meaningful* features) are not liable to be created a random background procedure [15-16]. Choosing whether a component is significant or not is based on the *number of false alarms* (NFA) which relates to the average number of such a feature anticipated from the background process (therefore “false alarms”) [15-16]. All the more absolutely, on account of real-valued features, if the features of interest are not prone to have a high value x, and given that the significant features are looked for among *N* features and then the NFA of the observed x is:

$\mathrm{NFA}(x) = N \Pr(X \geq x)$

where $\Pr(X \geq x)$ is the probability that a random feature X taking after the background process is larger than or equal to x.

In the case a NFA has been defined, the element of interest are in majority of papers those such that NFA ≤ 1

A. Algorithm

Input: an image ‘*i’*(size X×Y) and its Fourier transform ‘*I’*, patch size ‘*H’*

Step 1:

first extract non-overlapping independent patches of size H×H over entire image and obtain *P* patches. Then evaluate F_R using step 4.

Step 2:

Obtain the power spectra of patches for any (*n*, *m*) and obtain minimum value.

Step 3:

for any (*n*, *m*), obtain NFA value.

Step 4:

Consider the spike map M_o^P on H×H spectrum such that $M_o^P(n,m)=1$ if NFA $\left(\left|c_{n,m}\right|\right)\leq 1$ and 0 otherwise

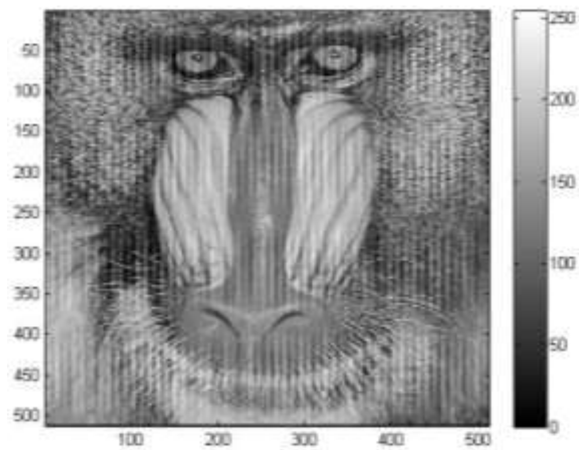
Step 5:

Interpolate the outlier map M_o^P of size H×H to X×Y providing map of M_o of the probable false spikes in the original image spectrum. Multiplying, the initial image spectrum by, $1-M_o$ acts as notch filter and thus eliminating quasi periodic noise.

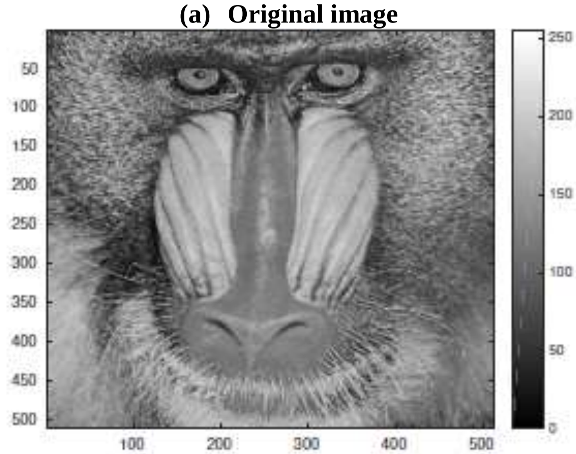
Step 6:

Retrieve $\hat{n}$, estimation of the periodic noise components as the inverse Fourier transform (IFT) of $M_o I$ and $\hat{i}$ estimation of de-noised image as, $i-\hat{n}$.

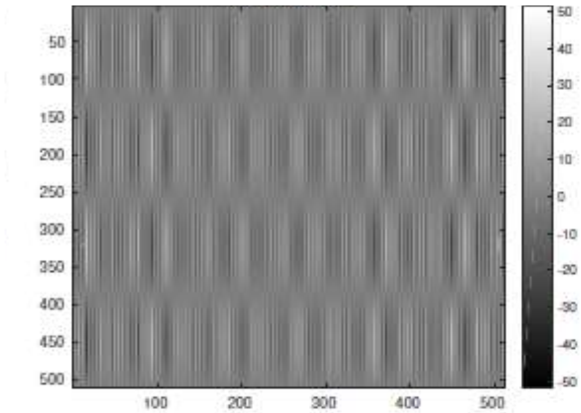
Results



(a) Original image



(b) Denoised image



(c) Noise Components

Figure 7: (a) Original image (b) noisy image (c) noisy component

In figure 7(a) original image corrupted with quasi-periodic noise is shown. In figure 7(b) de-noised image is shown, and an extracted noise component is shown in figure 7(c). It is evident from figure this approach reduces the noise level significantly.

5. CONCLUSIONS

Noise removal in an image is important and complicated problem due to the randomness of the noise. Most of the time noises are easily removed by measuring their pdfs. But in some cases estimation of noises is complicated which is superimposed on the signal spectral components. In such a case problem become complex as first, those frequency components has to be find out and careful removal of noise has to be done.

On the basis of results obtained in the paper, following conclusions can be made:

1. Due to the randomness of noise, filters needs to be carefully designed.
2. If pdfs of noises is known in advance, then filter design is not complex.
3. Quasi periodic noise can be removed using notch filter.
4. The concept of false alarm helps in detecting those spectral components which are corrupted with noise.
5. Noise spikes degrade the image severely.
6. Spectrum analysis helps us in finding out outliers.
7. Notch filter suppress the noise significantly.

REFERENCES

[1]. A. K. Jain, “Fundamentals of Digital Image Processing”, Prentice Hall of India, First Edition, 1989.

[2]. Rafael C .Gonzalez and Richard E. woods, “Digital Image Processing”, Pearson Education, Second Edition, 2005

[3]. K. S. Srinivasan and D. Ebenezer, “A New Fast and Efficient Decision-Based Algorithm for Removal of High-Density Impulse Noises,” IEEE Signal Processing Letters, Vol. 14, No. 3, March 2007.

[4] J. Benesty and J. Chen, Optimal Time-Domain Noise eduction Filters – A Theoretical Study, 1st ed. Springer, 2011, no. VII.

[5]. Suresh Kumar, Papendra Kumar, Manoj Gupta, Ashok Kumar Nagawat, “Performance Comparison of Median and Wiener Filter in Image De-noising” ,International Journal of Computer Applications (0975 – 8887) Volume 12– No.4, November 2010.

[6] Patil, J. & Jadhav S. (2013) “A Comparative Study of Image Denoising Techniques,” International Journal of Innovative Research in Science, Engineering and Technology, Vol. 2, No. 3.

[10] Dougherty G. (2010) “Digital Image Processing for Medical Applications,” second ed., Cambridge university press.

[11] Kamboj P. & Rani V., (2013) “A Brief study of various noise models and filtering techniques,” Journal of Global Research in Computer Science, Vol. 4, No. 4.

[12] Ashraf Abdel-Karim Helal Abu-Ein “A Novel Methodology for Digital Removal of Periodic Noise Using 2D Fast Fourier Transforms” Contemporary Engineering Sciences, Vol. 7, 2014, no. 3, 103 – 116.

[13]Mandeep Kaur, Dinesh Kumar, Ekta Walia, and Manjit Sandhu, “Periodic Noise Removal in Strain and Natural Images Using 2-D Fast Fourier Transform”, Interscience publication Vol 2, No.7, 2015

[14]Frederic Sur, “An a-contrario approach to quasi-periodic noise removal” Image Processing (ICIP), 2015 IEEE International Conference on image processing, 27-30 Sept. 2015.

[15] A. Oliva and A. Torralba, “Modeling the shape of the scene: a holistic representation of the spatial envelope,” Int. J. Comput. Vision. Vol. 42, No.3, pp.145–175, 2001.

[16] A. Torralba and A. Oliva, “Statistics of natural image categories,” Network Vol.14, No. 3, pp. 391–412, 2003.

