

An overview of the fundamental approaches that yield several image denoising techniques

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Abstract

Digital image is considered as a powerful tool to carry and transmit information between people. Thus, it attracts the attention of large number of researchers, among them those interested in preserving the image features from any factors that may reduce the image quality. One of these factors is the noise which affects the visual aspect of the image and makes others image processing more difficult. Thus far, solving this noise problem remains a challenge for the researchers in this field. A lot of image denoising techniques have been introduced in order to remove the noise by taking care of the image features; in other words, getting the best similarity to the original image from the noisy one. However, the findings are still inconclusive. Beside the enormous amount of researches and studies which adopt several mathematical concepts (statistics, probabilities, modeling, PDEs, wavelet, fuzzy logic, etc.), there is also the scarcity of review papers which carry an important role in the development and progress of research. Thus, this review paper introduce an overview of the different fundamental approaches that yield the several image-denoising techniques, presented with a new classification. Furthermore, the paper presents the different evaluation tools needed on the comparison between these techniques in order to facilitate the processing of this noise problem, among a great diversity of techniques and concepts.

Keywords: denoising methods, digital image, image denoising, image processing, noise

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1. Introduction

Among the different tools of communication between people, there is the image which carries a large amount of information. However, unfortunately, the image can be corrupted by parasitic information, which is called noise: an alteration of image, which may be caused by the image acquisition process or transmission [1, 2]. The main concern of the researchers in this subject is to succeed in solving this problem by removing noise from the noisy image and achieve the best restoration of the original one. To achieve the desired aim, they need ample and necessary knowledge, concepts and definitions, which are inspired from the review of relevant literature. Image processing is quite a wide field of knowledge due to its importance, and widely applied in several fields like biology, astronomy, industrial, medical and defence. Thus, a large amount of researches and studies have been done about this area. Where, among the existing barriers in restoring the corrupted image is the scarcity of review papers which carry an important role in the development and progress of research, In this paper we will take a closer look into the necessary information restricted in the primary phase of image processing (image pre-processing), called Image denoising, particularly the fundamental approaches of image denoising. We seek to gather and introduce these approaches and concepts smoothly, with good arrangement, where the readers can penetrate into the subject, in order to facilitate the path that leads to the goal, by making this paper a starting point of other studies concerning the image denoising. Thus, image, digital image, noise, noisy image, image denoising, approaches for image denoising, as well as method comparison, are presented in the rest of the paper by the following main sections. Section 2: discussion about relevant materials and tools, which present definitions and concepts about image, noise and filtering. Section 3: Discussion about the denoising methods, also the description of the basis of

denoising approaches. Section 4: both the evaluation and comparison of the denoising methods. Finally, section 5 offers the conclusion.

2. Materials and Tools

2.1. Image

An image is a scene representation through painting, sculptures, drawing, photography, and so on. It is also a structured set of information that, after the display on the screen, gives meaning to human. It may be defined as a two-dimensional function $I(x, y)$ analog brightness continuous, defined in a bounded domain, x and y as the spatial coordinates of a point of the image and I is a function of luminance intensity and color. In this aspect, the image is unusable by the machine, which requires digitization [3].

The digital image, in its broadest sense, refers to any image acquired, processed and stored in a coded form which may be represented by numbers (numerical values). Digitization is the process which permits the image to move from the physical state (optical image) represented by continuous signal (an infinity of intensity value), to the digital image state which is characterized by the discrete aspect (intensity take their values in a finite number of points). This is the digital form which permits a further exploitation by computer software tools. Thus, the digital image is a bounded set of elements, where each one of them is determined by location coordinate and value. These elements are named image elements, picture elements, pixels, and pels, whereas, the most widely used term to denote the digital image elements is "pixel". According to the luminance intensity value, digital image is classified into three types (color-coding): black and white gray scales and coloured scales.

The binary images are an array of integers ($k = 1$ bit), pixel that can take one of the values: 0 or 1. White is denoted by 0 and Black by 1. This is the simplest types of images and usually this kind is used to scan texts when the latter is composed of one color. The gray level is the value of the luminance intensity at one point. This image consists of only 8 bytes, and the pixel color can take values ranging from black to white through various levels of brightness [0, 1, 2, ..., 255]. Usually color images are based on three primary colours: Red, Green and Blue (RGB), and each of these colours use 8 bits for one pixel which takes a value from the range [0, 1, 2, ..., 255], so each pixel in the color image requires $3 \times 8 = 24$ bits to encode three components.

2.2. Noise

Noise is an alteration of image (parasites information) that may be created in one of these phases, during the acquisition process (conversion operation from optical signals to the electrical then from electrical to digital signal) through the transmission, sensor status and environmental conditions [1, 4]. The noise has different origins, but it causes similar effects such as the loss of sharpness in the details or the appearance of grains, where the amount of noise in noisy image is assigned by the number of corrupted pixels. In terms of removing this noise from the corrupted image, the researchers of this field have made some in-depth studies to know the nature and types of noise. The image is corrupted due to the fact that there are various types of noise such as the Gaussian noise, Poisson noise, Speckle noise, Salt and Pepper noise and many more fundamental noise types in the case of digital images [5].

Noise is integrated in the image $u(x, y)$ through three forms of noise $n(x, y)$, namely additive, multiplicative, and impulse noise [6, 7], to give a noisy image denoted by $v(x, y)$. The additive noise formula is shown by (1) :

$$v(x, y) = u(x, y) + n(x, y) \quad (1)$$

the multiplicative noise formula is modeled by (2):

$$v(x, y) = u(x, y) \times n(x, y) \quad (2)$$

3. Denoising Methods

Image denoising is a phase, which precedes the image processing (image pre-processing); in other words, a set of operations occurring on the image, which aims to ameliorate the visual aspect of the image by means of reducing or removing noise from image.

This is in order to facilitate other processes such as the compression, analyses, classification, segmentation, and extraction of information [8]. Denoising methods are based on the main idea which is to replace each corrupted pixel value (noise) in the noisy image with another value, making that image closer to the original one (noise free image) as much as possible, using the necessary knowledge about noise and image cited in the previous section. In other words, the denoising methods aim to achieve the version closest to the original image. Several methods have been developed in this way, although each method has its advantages and disadvantages. These denoising methods may be classified into two main categories, the spatial domain and transform domain filtering which merged together in some cases to yield hybrid filters.

3.1. Spatial Domain Filtering

Spatial domain filtering is considered as a traditional way to remove corrupted pixels (noise) from the image [9]. It is a set of mathematical operations that deal directly with the pixel in the image plane, because in this domain, the signal is represented by pixels, or in other words, image elements are pixels. The filtering operations are applied into these pixels, based on mathematics concepts, through which we apply the filtering window to each pixel in the whole noisy image (overall processing), in the case that the detection phase is absent, or to some pixels of noisy image (partial processing), or in the case that we firstly pass through the detection phase (Noise detection) using several detector techniques such as the fuzzy techniques as shown in Figure 1. Generally, the filter treats the noisy image through two ways, linear or non-linear as shown in Figure 1.

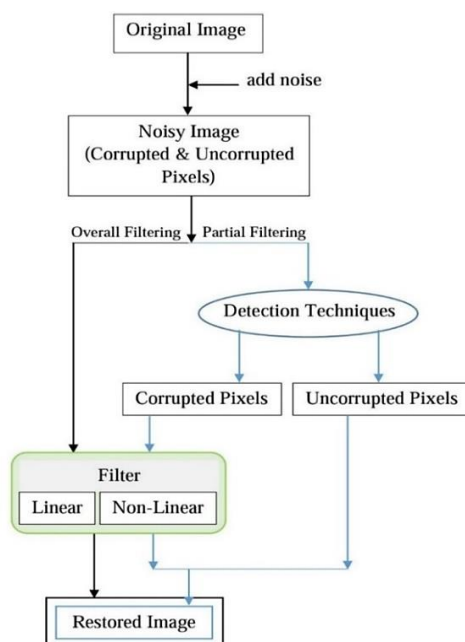


Figure 1. Basic path of spatial filtering process

3.1.1. Linear Filtering

The linear filter transforms an input data set into a set of output data according to a mathematical operation called convolution. It allows for each pixel in the area to which it applies, to change its value through a linear combination of its neighbors. The linear filtering operation is easy to implement for removing noise but usually it produces blurred images, which are the main defect of this filter [10, 11]. Many well known linear filters have been introduced like the mean filter and Wiener filter.

3.1.2. Non-linear Filtering

They are designed to solve the problems of the linear filter, especially with regard to the poor preservation of edges [10, 11]; Their principle is the same as the linear filters, where it

always replaces the value of each pixel with the calculated value from a mathematical operation applied to its neighbors' values, including itself. The difference is that this operation is no longer linear. There are many popular non-linear filters such as the median and its extensions (order statistic filters), bilateral filter, Total variation (TV), morphological filter, anisotropic filter and so on. Other characteristic filtering may differ between several denoising approaches, such as statistical/deterministic, adaptive/non-adaptive and local/non-local. In [12-15], some examples are presented.

3.2. Transform Domain Filtering

The transform domain filtering is the second category of image denoising approaches, which gained enormous interest from scholars and studies. It may be defined as a set of filtering operations that treats the image in another form (other domains) such as frequency domain (Figure 2), rather than the original form (original domain), in order to gain further information from the signal and reach a successful filtering through this new form. The new domain may differ from the original one in the dimensions (e.g. from 2D to 3D) or in the characteristics (e.g. from spatial to frequency domain). This transform is a mathematical conversion that is achieved through a clever mathematical tool (basis function). The image filtering process in the transform domain can split into two branches according to the type of this basis function [9]; adaptive to processed data and non-adaptive. For the adaptive approaches there are two effective techniques namely the Principal component analysis (PCA) [16], which treats only the data information given by the second-order statistics, and the Independent component analysis (ICA) [17] which comes as an extension to PCA to give better performance, by living up to high order statistics (the case of the most natural images) [18]. The main idea of both statistical techniques, PCA and ICA, is to use an orthogonal decomposition to separate linearly as much as possible the correlated data into independent sub-sets [19]. In the non-adaptive approaches there are many methods due to the variety of basic functions such as, wavelets [20], wave atoms [21], curvelets [22], contourlets [23], wedgelets [24], and bandelets [25], which transform the image to the frequency domain. From those, the oldest, the most popular, and the dominant one ("wavelet") [26], are highlighted in the following sections. Recently in the transform domain, a new efficient method (BM3D) is developed by Dabov et al. [27] using sparse 3D transform by grouping similar 2D-Blocks in the image into a 3D-arrays (grouped), in this case the image is represented in the transform domain by many 3D-groups. Then, the spectrum is shrunken to separate the noise from other features [28]. This method has shown great efficiency in removing image compared to several techniques, but in the case of high level of noise it gives less performance, and for that, in [29] a bounded BM3D method was proposed based on the basis BMED to exceed this limitation. Furthermore, many techniques were derived from the BM3D such as in [29], which focuses on the optimal choice of shrinkage operator, and the two algorithms in [30], CD-BM3D and iterative CD-BM3D used the complex domain. The several fundamental techniques of image denoising in transform domain are presented by the below diagram in Figure 3.

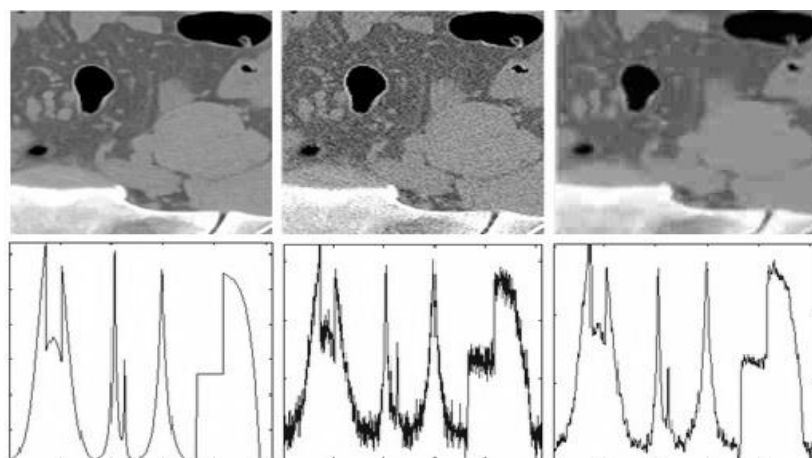


Figure 2. The above images transformed to the frequency domain below

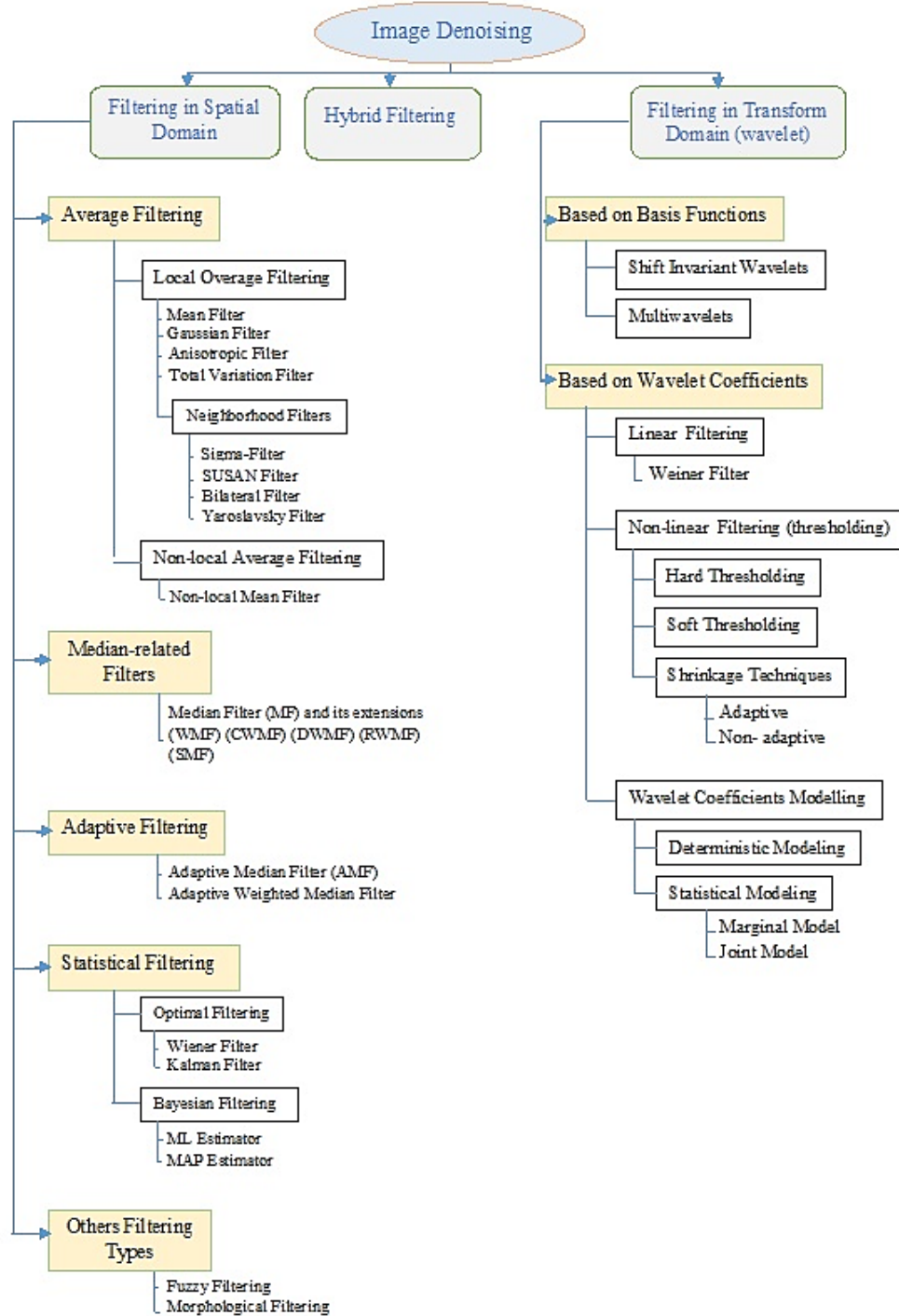


Figure 3. Image denoising approaches

3.3. Hybrid Filtering

Hybrid filtering may be considered as the third image-denoising category. It is a diverse combination of several approaches from the spatial or transform domain or both together as shown in Figure 3. This kind of image filtering, exploits the advantages of different existing filters to build a new filter which includes a mixture of these advantages, in order to overcome the limitations of conventional techniques and give better performance. This has been used by many researchers and studies in the image denoising. Thus, numerous hybrid filters have been proposed, whereby the point which attracts much attention, is the considerable attendance of

the wavelet in these hybrid filters. For example, in [31] the filter decomposes the image by (DT-CWT) then, it applies an adaptive wavelet thresholding to the detailed coefficients, while the approximation coefficients are treated by Non-Local Means (NLM) technique, and finally the denoised image is obtained by the inverse DT-CWT. As well, in [32] the undecimated wavelet transform (UDWT) and NLM is performed. In [33], a denoising technique based on the combination of wavelet transform and anisotropic filtering was presented. Many other hybrid filters use the mixture of wavelet and total variation has been introduced in [34-37]. The principle component analysis (PCA) was merged with the wavelet and NLM in [38] and [39], respectively. A hybrid neighborhood filter is applied in [40], based on the Gaussian filter with the correlation of wavelet coefficients. Wiener filtering was combined with DT-CWT and continuous wavelet transform (CWT) (to a seismic signal) in [41] and [42], respectively. The area in the image may be defined as a texture, edge or smooth (homogeneous) region [43]. If for each of these areas we chose the filter which gives good result among the existing filters, eventually we get three diverse filters for the image. This is the concept which is adopted in [43] by using the combination of three different multiresolution techniques, namely wave atoms (textures), curvelet (edges) and wavelet (smooth regions). Meanwhile, these last two techniques were blended in [44]. In [45], a hybrid filter including a mix of HMF (hybrid median filter) and total variation (TV) is proposed.

4. Evaluation and Comparison

The common objective of these introduced denoising methods is to remove noise from image by way of preserving its features, or in other words, reaching the restored image which is the most similar to the original one, taking into account certain strict and crucial criteria such as the simplicity of filter implementation and the cost merit [46]. Seeking to overcome filtering limitations and to achieve the optimality, a great number of denoising techniques have been introduced in these last years. Thus, many disparities and differences can be observed between these filters. Getting a comparison and evaluation from this large number proves to be an arduous task, especially as it shares many characteristics such as linear/non-linear, statistical/deterministic, etc. (network of features), therefore it is quite necessary to rely on some points linked with the three parts of the filtering process (Table 1) which are:

- a. The noisy image (input): the type of noise (additive, multiplicative, impulse noise, mixed noise), amount of noise (high, low), structure of image (texture, smooth, edge), pixels intensity.
- b. Filter (denoising tool): computational cost (acceptable, high), filter implementation (simple, complex).
- c. Restored image (output): the image quality is one of the evaluation criteria of denoising techniques performance, so the question is how do we assess this quality? The way by which the image quality is evaluated (evaluation criteria) may be divided into two ways:
 - The first one is the visual evaluation determined by the observer, where the human judgment is interested in the image components appearance, if it contains any degradation factors or otherwise, such as artifacts, discontinuities and blur [47].
 - The second one is the quantitative evaluation (quality metric) by using the measurement parameters, which include: 1) Signal to Noise Ratio (SNR), which measures the amount of noise n in the noisy image $I(i,j)$ using the standard deviation of the noise $\sigma(n)$ and image $\sigma(I)$ ($\sigma(I) = 60$ indicating good image quality) [48], it is given by (3); 2) Mean Squared Error (MSE), that measures the dissimilarity between the restored image $\hat{I}(i,j)$ and the original one $I(i,j)$ as shown below in (4), thus whenever the MSE is lower, the image denoising achieves more success [49]; 3) Peak Signal to Noise Ratio (PSNR) [50], a well-known parameter that has an inverse relationship with MSE, as denoted in (5).

It is not necessary to be an entailment relation between the visual and quantitative assessment, because sometimes an image, even with high PSNR or low MSE, does not seem clean. This means that these indexes (MSE, PSNR) are not well matched to perceived visual quality [51]. Thus, there are many quality assessment (QA) methods developed in the last decades, which take into account the human visual system (HVS), such as the Structural SIMilarity (SSIM) index [51].

$$SNR = \frac{\sigma(l)}{\sigma(n)} \tag{3}$$

$$MSE = \frac{1}{N} \sum_{i,j} (I[i, j] - \hat{I}[i, j])^2 \tag{4}$$

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \tag{5}$$

N the number of pixels in image.


By using these above three guidance points, the several techniques of image denoising can be evaluated and compared briefly according to their classification in Table 1 (field "types of filters"), as follows: The performance of filtering method rises from the left column to the right column and from the first row to the last row, where the performance of denoising method is denoted by the blue triangle, where it rises from the head to the base of this triangle. For example, the adaptive denoising methods in the transform domain are more efficient compared to the non-adaptive methods in the transform domain or with adaptive methods in the spatial domain. In addition, the linear filters are simple to implement than non-linear ones, whereas the statistical filters are expensive and complex compared to the deterministic filters.

5. Conclusion

This paper presents an overview of the fundamental approaches from which the several denoising algorithms are derived, as a starting point of future studies and researches in this subject. Through this study, it is found that there is an enormous number of denoising algorithms which makes the evaluation and the comparison between them difficult to be attainable. In order to overcome this situation by facilitating the understanding, the evaluation and the comparison between the significant number of diverse techniques of image denoising, this paper proposes seven categories to classify these algorithms (Linear/Nonlinear-Deterministic/Statistical-Non-Adaptive/Adaptive-Local/Non-Local-without Noise Detection (treat all pixels)/with Noise Detection (treat corrupted pixels)-Spatial Domain/Transform Domain-Unmixed/Hybrid), where the characteristics of any category affect the efficiency of the denoising filter. To achieve this goal, we also present the evaluation tools which permit the estimation of the efficiency and the disparity among these techniques. All these categories and evaluation tools are summarised in Table 1.

Table 1. The Comparison between Several Fundamental Denoising Methods

The noisy image (input)	Evaluation Tools		Filtering Types	
	Filter (denoising tool)	Restored image (output)		
- Type of noise (additive, multiplicative, impulse noise, mixed noise)	- Computational cost (acceptable, high)	- Measurement of noise (SNR, MSE, PSNR, etc.)	Linear	Non-Linear
- Amount of noise (high, low)	- Filter implementation (simple, complex)	- Visual quality (blur, artifacts, information loss, etc.)	Deterministic	Statistical
- Structure of image (texture, smooth, edge), pixels intensity			Non-Adaptive	Adaptive
			Local	Non-Local
			Without Noise Detection (treat all pixels)	With Noise Detection (treat corrupted pixels)
			Spatial Domain	Transform Domain
			Unmixed	Hybrid



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