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Image Denoising Techniques: Review

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Abstract- The search for efficient image denoising methods is still a valid challenge. Most algorithms have not yet attained a desirable level of applicability. Image denoising involves the manipulation of the image data to produce a visually high quality image. The importance of the image denoising could be a serious task for medical imaging, satellite and areal image processing, robot vision, industrial vision systems, micro vision systems, space exploring etc.The main aim of this paper is to examine various algorithms and understandingthe concept of denoising .

IndexTerms—Image noise, Image denoising,Translation invariance.

I. INTRODUCTION

Image denoising is a classical and flourishing research topic in image processing. The visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise.The received image needs processing before it can be used in applications.

Image denoising involves the manipulation of the image data to produce a visually high quality image. There are different types of noise models including additive and multiplicative. They include Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. The choice of the denoising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise present in the image so as to select the appropriate denoising algorithm. The filtering approach has been best when the image is corrupted with salt and pepper noise. The wavelet based approach finds applications in denoising images corrupted with Gaussian noise. In the case where the noise characteristics are complex, the multifractal approach can be used. A quantitative measure of comparison is provided by the signal to noise ratio of the image.

II. EVOLUTION OF IMAGE DENOISING TECHNIQUES

There is growing demand of image processing in diverse application areas such as multimedia computing, secured image data communication, biomedical imaging, biometrics, remote sensing, texture understanding, pattern recognition, compression etc.It is very essential to keep the useful data in the exact original form for further processing and translation invariant directionalframelet transform based denoising being the latest technique.This paper presents image denoising using various transforms.The directionality in the wavelet- or subband-based transform has been widely discussed over the past decades. The basic idea is that the representation should contain basiselements oriented at a variety of directions as much as possible while keeping the properties ofmultiresolution, localization,isotropy etc. as well[1].

E. J. Candes and D. L. Donoho [2] have proposedcurvelets which is well-known tool capturing the directional information.Thecurvelet transform is developed initially in the continuous domain via multiscale filtering.M. N. Do and M. Vetterli [3] have presented contourlets which is constructed in a discrete domain,thus leading to a fast implementation based on a Laplacian pyramid decomposition.

V. Velisavljevic, B. Beferull-Lozano, M. Vetterli, and P. L. Dragotti [4] have proposed directionlets for adapting both the wavelet filtering direction and the subsampling grid to the image feature orientation without resampling.Erwan Le Pennec and StéphaneMallat [5] have presented bandlets which decompose the image along multiscalevectors.The image decomposition inbandlet is implemented with a fast subband filtering algorithm.Runyi Yu [6] have presented dual tree complex wavelets characterized in terms of scaling filter relationship and wavelet filter relationship via the scaling transformation function.

Wang-Q Lim [7] has presented shearlet transform based on a simple and rigorous mathematical framework which not only provides a more flexible theoretical tool for the geometric representation of multidimensional data, but is also more natural for implementation.Theshearletapproach associated to a multiresolution analysis and this leads to a unified treatment of both the continuous and discrete world. However, all known constructions of shearlets so far are band-limited functions which have an unbounded support in space domain. In fact, in order to capture the local features of a given image efficiently, representation elements need to be compactly supported in the space domain. Furthermore, this property often leads to more convenient framework for practically relevant discrete implementation.

Truong T. Nguyen and SoontornOraintara [8] introduced a new uniformly, maximally decimated directional filter bank with six highpass directional subbands and two lowpasssubbands. The uniform directional filter bank implemented by a binary tree structure of two-channel filterbanks. The filterbank employed in the tree is shown to be aliasfree decimation and permissible.

Gerek and A.E.Cetin [9] have presented a 2D modification to the prediction part of lifting implementation of 5/3 wavelet. Chuo-Ling Chang and Bernd Girod [10] has estimates the adaptive directional lifting (ADL) transform which is different from the conventional 2-D lifting transform, the ADL is applied in the predicted direction as well as horizontal/vertical ones. Thus, adaptive directional lifting provides an efficient representation for images containing rich orientation features.

III. IMAGE DENOISING MODEL & NOISE TYPES

Image denoising can be formally defined as removal of noise present in the image while preserving the important and sharp features of the image. In acquiring, transmitting or processing a digital image for example, the noise induced degradationmay be dependent or independent of data which is shown in fig. 1

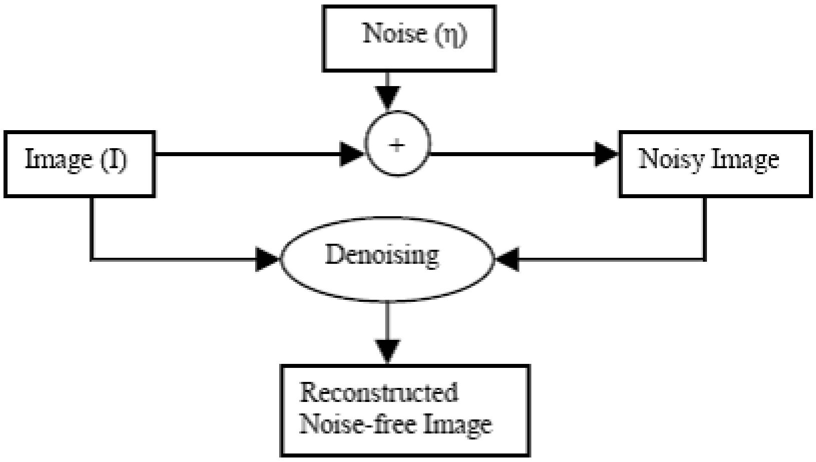

Fig. 1. Block diagram of Image DenoisingProcess[11]

A. Gaussian Noise

The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity.

B. Salt-And-Pepper Noise

Impulsive noise is sometimes called salt-and-pepper noise or spike noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc. Dead pixels in an LCD monitor produce a similar, but non-random, display. This can be eliminated in large part by using dark/bright pixels.

C. Film Grain

Film grain is usually regarded as a nearly isotropic (non-oriented) noise source; its effect is made worse by the distribution of silver halide grains in the film also being random.

D. Shot Noise

Shot noise is the dominant noise in the lighter parts of an image.The shot noise is caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level.Shot noise has a root-mean-square value proportional to the square root of the image intensity, and the noises at different pixels are independent of one another. Shot noise follows a Poisson distribution, which is usually not very different from Gaussian. In addition to photon shot noise, there can be additional shot noise from the dark leakage current in the image sensor; this noise is sometimes known as "dark shot noise" or "dark-current shot noise".

E. Quantization Noise

The noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise; it has an approximately uniform distribution, and can be signal dependent, though it will be signal independent if other noise sources are big enough to cause dithering, or if dithering is explicitly applied. This error is either due to rounding or truncation. The error signal is sometimes considered as an additional random signal called quantization noise because of its stochastic behaviour.

F. Anisotropic Noise

Some noise sources show up with a significant orientation in images. For example, image sensors are sometimes subject to row noise or column noise. Anisotropic noise textures are interesting for many visualization and graphics applications. The spot samples can be used as input for texture generation, e.g., Line Integral Convolution (LIC), but can also be used directly for visualization by itself. They are especially suitable for the visualization of tensor fields that can be used to define a metric for the anisotropic density field. We present a novel method for generating stochastic samples to create anisotropic noise textures consisting of non-overlapping ellipses, whose size and density match a given metric. Our method supports an automatic packing of the elliptical samples resulting in textures similar to those generated by anisotropic reaction-diffusion.

G. Speckle Noise

Speckle noise is a multiplicative noise. This type of noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR(Synthetic Aperture Radar) imagery[12]. The source of this noise is attributed to random interference between the coherent returns.

IV. CLASSIFICATION OF DENOISING ALGORITHMS

A. Spatial Filtering

A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters.

1) Non-Linear Filters

With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible.In recent years, a variety of nonlinear mediantype filters such as weighted median [13], rank conditioned rank selection [14], and relaxed median [15] have been developed to overcome this drawback.

2)Linear Filters

A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise. The wiener filtering[16] method requires the information about the spectra of the noise and the original signal and it works well only if the underlying signal is smooth.. To overcome the weakness of the Wiener filtering, Donoho and Johnstone proposed the wavelet based denoising scheme in [17, 18].

B. Transform Domain Filtering

The transform domain filtering methods subdivided according to the choice of the basis functions as data adaptive and non-adaptive.

1)Non-AdaptiveData Transform

a.Spatial-Frequency Filtering

Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods the removal of the noise is achieved by designing a frequency domain filter and adapting a cut-off frequency when the noise components are decorrelated from the useful signal in the frequency domain. These methods are time consuming and depend on the cut-off frequency and the filter function behavior.

b.Wavelet domain Filtering

Operations in the wavelet domain can be subdivided into linear and nonlinearmethods.

- *Linear Filters*

Linear filters such as Wiener filter in the wavelet domain yield optimal results when the signal corruption can be modeled as a Gaussian process and the accuracy criterion is the mean square error (MSE).

- *Non-Linear Filtering*

The procedure exploits sparsity property of the wavelet transform and the fact that the Wavelet Transform maps white noise in the signal domain to white noise in the transform domain. Thus, while signal energy becomes more concentrated into fewer coefficients in the transform domain, noise energy does not. It is this important principle that enables the separation of signal from noise.

c. Wavelet Coefficient Model

The wavelet coefficient model focuses on the multiresolution properties of Wavelet Transform. This technique gives correlation of signal at different resolutions by observing the signal across multiple resolutions. This method produces excellent output but is computationally much more complex and expensive. The modeling of the wavelet coefficients can either be deterministic or statistical.

- *Deterministic method*

The Deterministic method of modeling involves creating tree structure of wavelet coefficients with every level in the tree representing each scale of transformation and nodes representing the wavelet coefficients. The optimal tree approximation displays a hierarchical interpretation of wavelet decomposition. Wavelet coefficients of singularities have large wavelet coefficients that persist along the branches of tree.

- *Statistical Modeling of Wavelet Coefficients*

This approach focuses on properties of the Wavelet Transform such as multiscale correlation between the wavelet coefficients, local correlation between neighborhood coefficients etc. This approach has an inherent goal of perfecting the exact modeling of image data with use of Wavelet Transform

2)*Data-Adaptive Transforms*

Recently a new method called Independent Component Analysis (ICA)[19] has gained wide spread attention. One advantage of using ICA is it's assumption ofsignal to be Non-Gaussian which helps denoising of images with Non-Gaussian as well as Gaussian distribution. Some applications of ICA method are machine fault detection, seismic monitoring, reflection cancelling, finding hidden factors in financial data text document analysis, radio communications, audio signal processing, image processing, data mining, time series forecasting, defect detection in patterned display surfaces, bio medical signal processing. Disadvantage of ICA based methods is the computational cost because it uses a sliding window

V. CONCLUSION

In this paper, we explored some of the denoising techniques for image denoising. Here we analyzed and present a literature review of some of the proposed denoising techniques that will be useful for the users by getting a brief introduction of these techniques so that they can make use of any one of them if needed. Image processing is a widely growing field as many of the nowadays applications are making use of it. Therefore, there is also a need of image denoising techniques due to introduction of noisy elements during image acquisition. Hence, our concern is to provide a collective brief review of some of these techniques in a single paper to provide ease to the image users

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