Comparative Analysis of Image Denoising by Filtering Techniques

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Abstract---Digital images are noisy due to ecological disturbances and it is degrade the quality of images. Data sets collected by image sensors are generally infected by noise and it is due to imperfect instruments. The noise is characterized by its pattern and by its probabilistic characteristics. There is a wide variety of noise types while we focus on the most important types of noises and comparative analysis of denoising techniques for corrupted images to enhance image quality is discussed in this paper. There have been several published algorithms and each approach has its assumptions, advantages and limitations. This paper presents a review of some significant work in the area of image denoising in terms of PSNR and ENL with different noise level.

Keywords: Denoising, PSNR, SD, MSE, Filtering Methods

I. INTRODUCTION

IMAGE denoising is still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This paper describes different methodologies for noise reduction in terms of PSNR comparison giving an insight as to which technique should be used to find the most reliable estimate of the original image data given its degraded version. Noise modeling in images is greatly affected by capturing instruments, data transmission media and discrete sources of radiation such cameras. [1-6].

Generally noise is introduced in the image during image transmission. Depending on the type of the noise, the degradation of the image will vary. According to the percentage of image quality degradation, the noise removal techniques must be chosen. The traditional methods of noise removal include filters, Total Variation (TV) method, Shrinkage models and different transforms are discussed [].

A. Noise Model and characteristic [1-2, 7-9]

Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise is observed in ultrasound images whereas Rician noise affects MRI images. The scope of the paper is to focus on noise removal techniques for natural images. Imaging sensors can be affected by ambient conditions. Interference can be added to an image during transmission. We can consider a noisy image to be modeled as follows: $g(x, y) = f(x, y) + \eta(x, y)$ (1.1)

Where $f(x, y)$ is the original image pixel, $\eta(x, y)$ is the noise term and $g(x, y)$ is the resulting noisy pixel. If we can estimate the model the noise in an image is based on this will help us to figure out how to restore the image. Although these unwanted fluctuations became known as "noise" by analogy with unwanted sound they are inaudible and actually beneficial in some applications, such as irresolute.

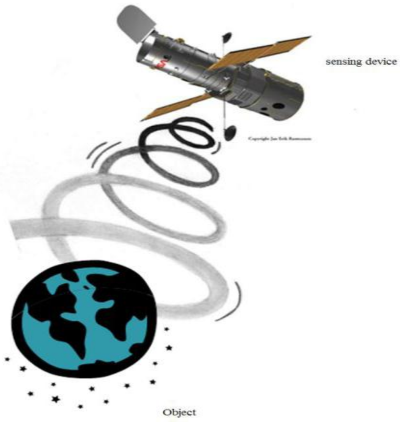

Fig. 1: Noise Model.

B. Gaussian noise - The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity, caused primarily by Johnson-Nyquist noise (thermal noise), including that which comes from the reset noise of capacitors. In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel. Amplifier noise is a major part of the read noise of an image sensor, that is, of the constant noise level in dark areas of the image.

C. Salt-and-pepper noise - Impulsive noise is sometimes called salt & 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.

D. Shot noise - The dominant noise in the lighter parts of an image from an image sensor is typically that caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level; this noise is known as photon shot noise. 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.

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 behavior.

High levels of noise are almost always undesirable, but there are cases when a certain amount of noise is useful, for example to prevent discretization artifacts. Some noise also increases apparent sharpness. Noise purposely added for such purposes are called either it improves the image perceptually or it degrades the signal-to-noise ratio.

II. CLASSIFICATION OF DENOISING TECHNIQUES

As shown in Fig. 2, there are two basic approaches to image denoising, spatial filtering methods and transform domain filtering methods.

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 and 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 median type filters such as weighted median, rank conditioned rank selection, and relaxed median 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 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 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. Wiener method implements spatial smoothing and its model complexity control correspond to choosing the window size.

B. *Transform Domain Filtering*

The transform domain filtering methods can be subdivided according to the choice of the basic functions. The basic functions can be further classified as data adaptive and non-adaptive.

1) 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 uncorrelated 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.

2) Wavelet domain - Filtering operations in the wavelet domain can be subdivided into linear and nonlinear methods.

3) 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). However, designing a filter based on this assumption frequently results in a filtered image that is more visually displeasing than the original noisy signal, even though the filtering operation successfully reduces the MSE. In a wavelet-domain spatially adaptive FIR Wiener filtering for image denoising is proposed where wiener filtering is performed only within each scale and intrascale filtering is not allowed.

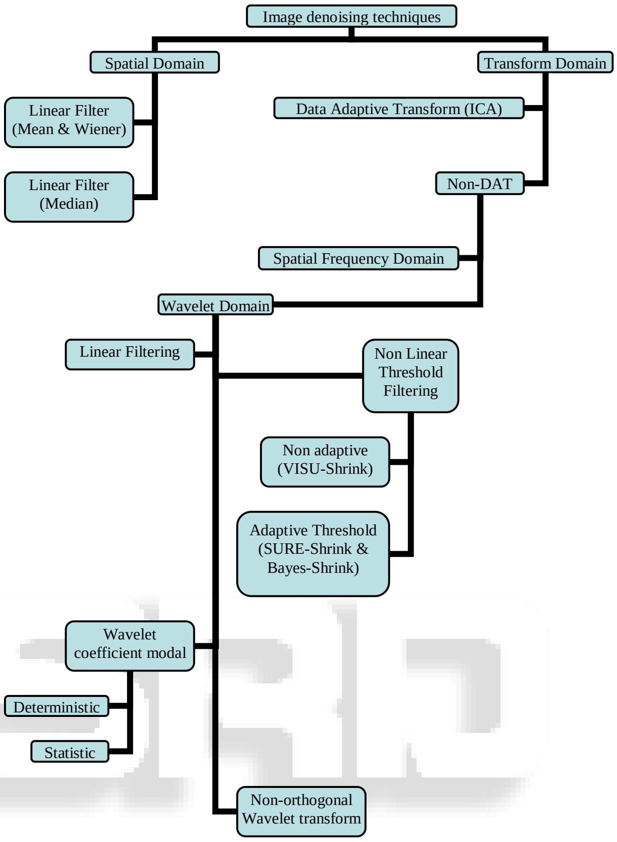

Fig. 2: Classification of denoising techniques

4) Non-Linear Threshold Filtering - The most investigated domain in denoising using Wavelet Transform is the non-linear coefficient thresholding based methods. Thus, while signal energy becomes more concentrated into fewer coefficients in the transform domain, noise energy does not. It is important principle that enables the separation of signal from noise. The procedure in which small coefficients are removed while others are left untouched is called Hard Thresholding. But the method generates false blips, better known as artifacts, in the images as a result of unsuccessful attempts of removing reasonably large noise coefficients. To overcome the demerits of hard thresholding, wavelet transform using soft thresholding was also introduced. In this scheme, coefficients above the threshold are reduced in size by the absolute value of the threshold itself.

5) Non-Adaptive thresholds - VISU-Shrink - It is non-adaptive universal threshold, which depends only on number of data points. It has asymptotic equivalence suggesting best performance in terms of MSE when the number of pixels reaches infinity. VISU-Shrink is known to yield overly smoothed images because its threshold choice can be unwarrantedly large due to its dependence on the number of pixels in the image.

6) Adaptive Thresholds - SURE-Shrink - It uses a hybrid of the universal threshold and the SURE [Stein's Unbiased

Risk Estimator] threshold and performs better than VISU-Shrink. BayesShrink minimizes the Bayes' Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold. BayesShrink outperforms SURE-Shrink most of the times.

7) Bayes-Shrink - The main objective of this algorithm is to minimize the Bayesian risk and hence its name, Bayes-Shrink. Its denoising performance is poor in high density additive white Gaussian noise.

8) Bi-Shrink - This method is based on new non-gaussian bivariate distributions to model inter scale dependencies. A nonlinear bivariate shrinkage function using the Maximum a Posteriori (MAP) estimator is derived. In a second paper, these authors have extended their approach by taking into account the intrascale variability of wavelet coefficients. Its denoising performance is deteriorates in high density additive white gaussian noise.

III. IMAGE ASSESSMENT PARAMETERS [1, 7-10]

Image quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an important problem.

In digital or film-based photography, an image is formed on the image plane of the camera and then measured electronically or chemically to produce the photograph. The image formation process may be described by the ideal pinhole camera model, where only light rays from the depicted scene that pass through the camera aperture can fall on the image plane. In reality, this ideal model is only an approximation of the image formation process, and image quality may be described in terms of how well the camera approximates the pinhole model.

A. *Mean squared error (MSE)*

The mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y_i} - Y_i)^2. \tag{3.1}$$

B. *Peak signal-to-noise ratio (PSNR)*

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \tag{3.2}$$

IV. RESULT AND DISCUSSION

Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), Mean Square Error (MSE) as well as in terms of visual quality of the images. Many of the current techniques assume the noise model to be Gaussian. In reality, this assumption may not always hold true due to the varied nature and sources of noise. An ideal denoising procedure requires a priori knowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise model. Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms. Such models can be effectively used for image denoising and compression.

Fig. 3 and Fig. 4 shows Comparison of different denoising techniques in terms of image assessment parameters and employed technique in reference 8 has been better PSNR values compared to other techniques.

A literature survey for different image denoising techniques was done. Proposed method can provide better results in terms of image quality and similarity measures. Future scope is to calculate the amount of noise added to the pixel, removal of noise and evaluating the signal to noise ratio. It is expected that the future research will focus on SVD and it will be effectively used for image denoising and compression.

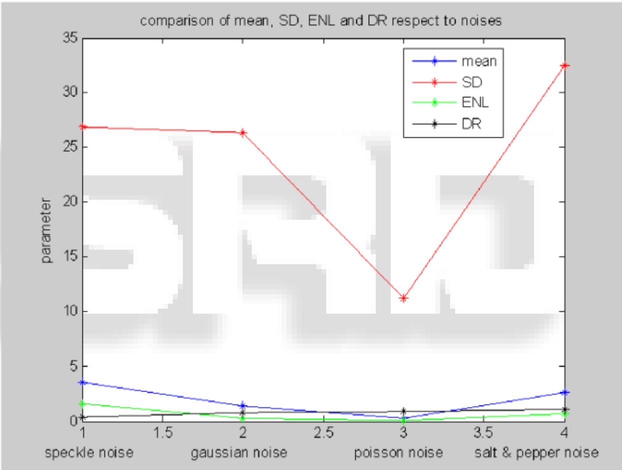

Fig. 3: MSE, SD and PSNR Comparison of denoising techniques

Fig. 3: Comparison of image denoising method

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