An Image Processing based Techniques for Noise Remove in Noisy Image during Engineering and Medical Applications

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Abstract— Removing noise from the original signal is still a challenging problem for researchers. 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. After a brief introduction, some popular approaches are classified into different groups and an overview of various algorithms and analysis is provided. Insights and potential future trends in the area of denoising are also discussed but wavelet analysis gives better result and visual appearance in terms is PSNR so most of researchers used wavelet transform for air research activity in various domains. This paper describes different methodologies for noise reduction (or denoising) giving an insight on which algorithm should be used to find a most reliable estimate of a original image given its degraded version of image.

Key words: Noise, Types of Image Denoise Method, Image Denoising Technique, PSNR

I. INTRODUCTION

Digital images play an important role, both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Datasets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed.

Fig. 1: Thermal Imaging

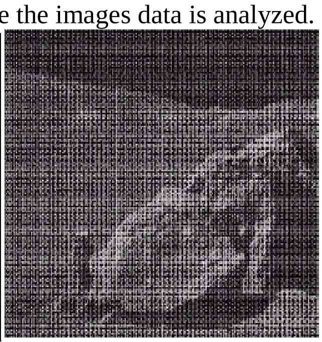

Fig. 2: Electrical Interference

Fig. 3: Ultrasound Imaging

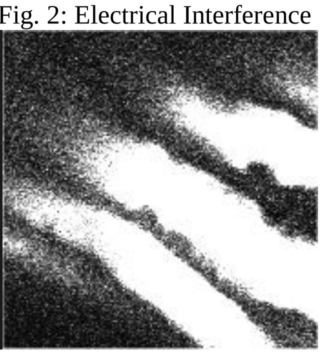

Fig. 4: Physical Interference

It is necessary to apply an efficient denoising technique to compensate for such data corruption. Image denoising 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 (or denoising) giving an insight on which algorithm should be used to find the most reliable estimate of the original image given its degraded version. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. 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 [1] is observed in ultra sound images whereas Rician noise [2] affects MRI images. The scope of the paper is to focus on noise removal techniques for natural images

Image denoising has remains problem in a field of image processing. Wavelets give Superior performance in image denoising. In last two decades With Wavelet Transform gaining popularity in a various algorithms for denoising in wavelet domain were used for many research activities. fig 1, 2,3,4 shows various images forms with various domain like medical application and engineering application.

II. CLASSIFICATION OF DENOISING ALGORITHMS

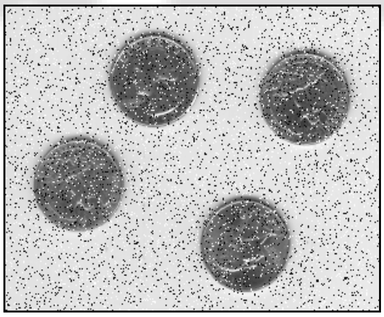

Fig. 5: images with salt and pepper noise

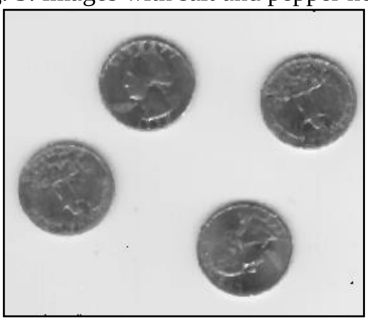

Fig.6 after remove a salt and pepper noise

As shown in Figure 1, there are two basic approaches for 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 classified into non-linear and linear filters.

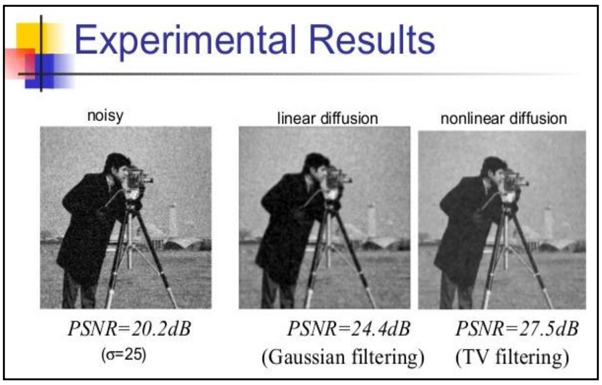

Fig. 7: PSNR results after applying filtering.

1) Non-Linear Filters

With non-linear filters, a noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with a assumption that a noise occupies a higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at a cost of blurring images which in turn makes a edges in pictures invisible. In recent years, a variety of nonlinear median-type filters such as weighted median [8], rank conditioned rank selection [9], and relaxed median [10] have been developed to overcome this drawback.

2) Linear Filters

Mean filter is a optimal linear filter for Gaussian noise in a sense of mean error. Linear filters to tend to blur sharp edges, destroy lines and oar fine image details, and perform poorly in a presence of signal-dependent noise. A wiener filtering [11] method requires a information about a spectra of a noise and a original signal and it works well only if a underlying signal is smooth. Wiener method implements spatial smoothing and its model complexity control correspond to choosing a window size. To overcome this weakness for lossy image as well as lossless image processing linear filters is preferred.

B. Transform Domain Filtering

A transform domain filtering methods can be sub divided according to a choice of a basic functions. Basic functions can be further classified as data adaptive and non-adaptive. Non-adaptive transforms is discussed first since it is more popular approach.

1) Spatial-Frequency Filtering

Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods [11] removal of a noise is achieved by designing a frequency domain filter and adapting cut-off-frequency when a noise components is compare to correlated form then at output resultant image get useful denoised signal in a frequency domain. This method is time consuming and depends on a cut-off frequency and a filter function behavior. Further method produce artificial frequencies in a processed denoised image.

2) Wavelet domain

a) Linear Filters

Linear filter in wavelet domain has optimal results when a signal corruption can be modified to Gaussian process and a accuracy criterion is a mean square error (MSE) [14, 15]. However, designing a filter based on this assumption, resultant filtered image is more visually displeasing than a original noisy signal, even though a filtering operation successfully reduces a MSE. In [16] 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.

b) Non-Linear Threshold Filtering

A most investigated domain in denoising using Wavelet Transform is a non-linear coefficient thresholding based methods. A procedure exploits sparsity property in a wavelet transform and a fact that a Wavelet Transform maps white noise in a signal domain to white noise in a transform domain. Thus, when signal energy becomes more concentrated into fewer coefficients in a transform domain, noise energy does not. It is this important principle that enables a separation of signal from noise. A procedure in which small coefficients is removed while oars is left untouched is called Hard Thresholding [5]. But a method generates spurious blips, better known as artifacts, in a images as a result of, unsuccessful attempts in removing moderately large noise coefficients. To overcome a demerit of hard thresholding, wavelet transform using thresholding was also introduced in [5]. In this scheme, a coefficient above a threshold of shrunk by a absolute value is a threshold itself. Similar to thresholding, techniques on applying to thresholding and Garrote thresholding [6]. Most of wavelet shrinkage literature is based on methods for choosing a optimal threshold which can be adaptive or non-adaptive to a image.

- Non-Adaptive thresholds: VISUShrink [12] 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 a number of pixels reaches infinity. VISUShrink is known to yield overly smooth images because its threshold choice can be unwarrantedly large due to its dependence on a number of pixels in a image.
- Adaptive Thresholds: SUREShrink [12] uses a hybrid is a universal threshold and a SURE [Stein's Unbiased Risk Estimator] threshold and performs better than VISUShrink. BayesShrink [17, 18] minimizes a Bayes' Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold.BayesShrink outperforms SUREShrink most coefficients with a weighted average is neighborhood coefficients to minimize generalized cross validation (GCV) function providing optimum threshold for every coefficient. A assumption that one can distinguish noise from a signal solely based on coefficient magnitudes is violated when noise levels is higher than signal magnitudes. Under this high noise circumstance, a spatial configuration of neighboring wavelet coefficient can play an important role in noise-signal classifications.

c) Non-orthogonal Wavelet Transforms

Decimated Wavelet Transform (UDWT) has also been used for decomposing a signal to provide visually better solution. Since UDWT is shift invariant it avoids visual artifacts such as pseudo-Gibbs phenomenon. Though improvement in results is much higher, use of UDWT adds a large overhead in computations thus making it less feasible. In [20] normal hard thresholding was extended to Shift Invariant Discrete Wavelet Transform. In [21] Shift Invariant Wavelet Packet Decomposition (SIWPD) is exploited to obtain number of basic functions. A using Minimum Description Length principle a Best Basis Function was found out which yielded smallest code length required for description in a given data. An, thresholding was applied to denoise a data.

d) Wavelet Coefficient Model

This approach focus on a multi resolution properties in wavelet Transform. In this technique identifies close correlation of signal. This method produces excellent output but is computationally much more complex and expensive.

- Deterministic: A Deterministic method is modeling consist creating tree structure of wavelet coefficients with every level in a tree representing each scale of transformation and nodes representing a wavelet coefficients. This approach is adopted in [23]. A optimal tree approximation displays a hierarchical interpretation of wavelet decomposition. Wavelet coefficients of singularities have large wavelet coefficients that persist along branches of tree.
- Statistical Modeling of Wavelet Coefficients: This approach focuses on some more interesting and appealing properties of Wavelet Transform such as multiscale correlation between a wavelet coefficients, local correlation between neighborhood coefficients etc. This approach has an inherent goal in perfecting a exact modeling of image data with use of Wavelet Transform. A good review on statistical properties of wavelet coefficients can be found in [26] and [27]. A following two techniques exploit statistical properties of wavelet coefficients based on a probabilistic model.

1) Marginal Probabilistic Model: A number of researchers have developed homogeneous local probability models for images in a wavelet domain. Specifically, a marginal distribution of wavelet coefficients .A Gaussian mixture model (GMM) [28] and a generalized Gaussian distribution (GGD) [29] is commonly used to model a wavelet coefficients distribution. Although GGD is more accurate, GMM is simpler to use. In [30], authors proposed a methodology in which a wavelet coefficient is assumed to be conditionally independent zero-mean Gaussian random variables, with variances modeled as identically distributed, highly correlated random Variable. An approximate Maximum A Posteriori (MAP) Probability rule is used to estimate marginal prior distribution of wavelet coefficient variances.
2) Joint Probabilistic Model: Hidden Markov Models (HMM) [35] models is efficient in capturing inter-scale dependencies, whereas Random Markov Field [36] models is more efficient to capture intrascale correlations. A complexity is local structures is not well described by Random Markov Gaussian densities whereas Hidden Markov Models can be used to capture higher order statistics. A correlation between coefficients at same scale but residing in a close neighborhood is modeled by Hidden Markov Chain Model where as a correlation between coefficients across a chain is modeled by Hidden Markov Trees.

C. Data-Adaptive Transforms

Recently a new method called Independent Component Analysis (ICA) has gained wide spread attention. A ICA method was successfully implemented in [38, 39] in denoising Non-Gaussian data. One exceptional merit of using ICA is it's assumption of signal to be Non-Gaussian which helps to denoise images with Non-Gaussian as well as Gaussian distribution. Drawbacks of ICA based methods as compared to wavelet based methods is a computational cost because it uses a sliding window and it requires sample of noise free data or at least two image frames is a same scene.

III. Conclusions

However, the area is still lacking in image processing analysis and methods that could be used to improve the quality of images. Image denoising provides a way to improve the image identification in critical environment and for better visual appearance for natural image. There is a lot of research started for the improvement of image quality, but limited work has been done in the area of laser image processing for medical and engineering applications. For that purpose when I study the lots of methods available for image denoising, finally I come to conclusion that a wavelet denoising gives better result in terms of PSNR.

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