A Literature Survey on Domain Image Denoising Techniques

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Abstract: - Digital images play an important role both in daily life applications such as satellite television, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. In reality, an image is mixed with certain amount of noise which decreases visual quality of image. Therefore, removal of noise in an image is a very common problem in recent research in image processing. An image gets corrupted with noise during acquisition or at transmission due to channel errors or in storage media due to faulty hardware. Removing noise from the noisy image is still a challenging problem for researchers. Removal of noise is an important step in the image restoration process, but denoising of image remains a challenging problem in recent research associate with image processing. Denoising is used to remove the noise from corrupted image, while retaining the edges and other detailed features as much as possible. 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. In this review paper the various image denoising methods have been analyzed..

Keywords- Image denoising, contourlet transform, Bessel k-form distribution, Bayesian estimator.

I. INTRODUCTION

A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained. Degradation comes from blurring as well as noise due to electronic and photometric sources. Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contributes to the degradation.

Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality.

Binary images are the simplest type of images and can take only two discrete values, black and white. Black is represented with the value ‘0’ while white with ‘1’. Note that a binary image is generally created from a gray-scale image. A binary image finds applications in computer vision areas where the general shape or outline information of the image is needed. They are also referred to as 1 bit/pixel images.

Gray-scale images are known as monochrome or one-color images. The images used for experimentation purposes in this study are all gray-scale images. They contain no color information. They represent the brightness of the image. This image contains 8 bits/pixel data, which means it can have up to 256 (0-255) different brightness levels. A ‘0’ represents black and ‘255’ denotes white. In between values from 1 to 254 represent the different gray levels. As they contain the intensity information, they are also referred to as intensity images.

Color images are considered as three band monochrome images, where each band is of a different color. Each band provides the brightness information of the corresponding spectral band. Typical color images are red, green and blue images and are also referred to as RGB images. This is a 24 bits/pixel image.

About "Image Processing"

In computer science, "image processing" refers to any form of signal processing for which the input is an image. The output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

Application of image processing methods

The wide use of digital photos in recent years created the need to use a variety of procedures that utilize methods for image representation and processing. Some of these applications are:

- Compression. The image quality of digital cameras has greatly improved in recent years. As a result, the size of image files has increased dramatically when classic methods of image representation are used. In order to reduce the file size of these images, compression methods have to be utilized.
- Photographic processing. With the adoption of digital photography as the mainstream photography method, a variety of image processing tasks are needed for the images taken. Tasks like, resizing, enlargement, shrinking, rotation, coloring, brightness adjusting, scaling, etc.
- Content based image retrieval. The creation of databases with thousands of images indexed based on their textures structural and textural characteristics require the use of feature extraction methods as a means of comparison and identification.
- Texture classification. Many methods have been proposed in literature for texture classification. Applications of these methods vary from detection of forest and urban areas from aerial photos to detection of tumors in medical ultrasound images.

Additive and Multiplicative Noises

Note that 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. Typical images are corrupted with noise modeled with either a Gaussian, uniform, or salt or pepper distribution. Another typical noise is a speckle noise, which is multiplicative in nature.

Noise is present in an image either in an additive or multiplicative form. An additive noise follows the rule

$$w(x, y) = s(x, y) + n(x, y),$$

while the multiplicative noise satisfies

$$w(x, y) = s(x, y) \times n(x, y),$$

where s(x,y) is the original signal, n(x,y) denotes the noise introduced into the signal to produce the corrupted image w(x,y), and (x,y) represents the pixel location. The above image algebra is done at pixel level. Image addition also finds applications in image morphing. By image multiplication, we mean the brightness of the image is varied.

The digital image acquisition process converts an optical image into a continuous electrical signal that is, then, sampled. At every step in the process there are fluctuations caused by natural phenomena, adding a random value to the exact brightness value for a given pixel.

Gaussian Noise

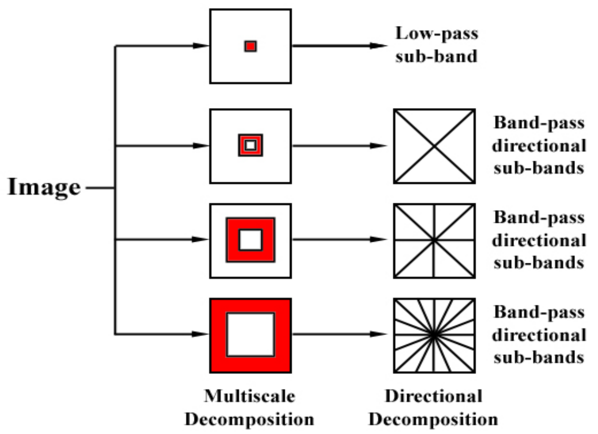
Gaussian noise is evenly distributed over the signal. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2}$$

distribution, which has a bell shaped probability distribution function given by, where g represents the gray level, m is the mean or average of the function, and ois the standard deviation of the noise.

II. SYSTEM MODEL

To retain the directional and multiscale properties of the transform, the Laplacian Pyramid was replaced with a nonsubsampled pyramid structure to retain the multiscale property, and a nonsubsampled directional filter bank for directionality.



The first major notable difference is that upsampling and downsampling are removed from both processes. Instead the filters in both the Laplacian Pyramid and the directional filter banks are upsampled. Though this mitigates the shift invariance issue a new issue is now present with aliasing and the directional filter bank. When processing the coarser levels of the pyramid there is potential for aliasing and loss in resolution. This issue is avoided though by upsampling the directional filter bank filters as was done with the filters from the pyramidal filter bank. [4]

The next issue that lies with this transform is the design of the filters for both filter banks. According to the authors there were some properties that they desired with this transform such as: perfect reconstruction, a sharp frequency response, easy implementation and linear-phase filters. These features were implemented by first removing the tight frame requirement and then using a mapping to design the filters and then implementing a ladder type structure. These changes lead to a transform that is not only efficient but performs well in comparison to other similar and in some cases more advanced transforms when denoising and enhancing images.

III. LITERATURE REVIEW

H. Sadreazami, M. O. Ahmad and M. N. S. Swamy, [1] Statistical image modeling has attracted great attention in the field of image denoising. In this work, a new image denoising method in the contourlet domain is introduced in which the contourlet coefficients of images are modeled by using the Bessel k-form prior. A noisy image is decomposed into a low frequency approximation sub-image and a series of high frequency detail sub-images at different scales and directions via the contourlet transform. To estimate the noise-free coefficients in detail subbands, a Bayesian estimator is developed utilizing the Bessel k-form distribution. In order to estimate the parameters of the distribution, a characteristic function-based technique is used. Simulation results on standard test images show improved performance both in visual quality and in terms of the peak signal-to-noise ratio and structural similarity index as compared to some of the existing denoising methods. The proposed method also achieves an excellent balance between noise suppression and details preservation.

H. Sadreazami, M. O. Ahmad and M. N. S. Swamy, [2] A new contourlet-based method is introduced for reducing noise in images corrupted by additive white Gaussian noise. It is shown that a symmetric normal inverse Gaussian distribution is more suitable for modeling the contourlet coefficients than formerly-used generalized Gaussian distribution. To estimate the noise-free coefficients, a Bayesian maximum a posteriori estimator is developed utilizing the proposed distribution. In order to estimate the parameters of the distribution, a moment-based technique is used. The performance of the proposed method is studied using typical noise-free images corrupted with simulated noise and compared with that of the other state-of-the-art methods. It is shown that compared with other denoising techniques, the proposed method gives higher values of the peak signal-to-noise ratio and provides images of good visual quality.

H. Sadreazami, M. O. Ahmad and M. N. S. Swamy, [3] In the past decade, several schemes for digital image watermarking have been proposed to protect the copyright of an image document or to provide proof of ownership in some identifiable fashion. This paper proposes a novel multiplicative watermarking scheme in the contourlet domain. The effectiveness of a watermark detector depends highly on the modeling of the transform-domain coefficients. In view of this, authors first investigate the modeling of the contourlet coefficients by the alpha-stable distributions. It is shown that the univariate alphastable distribution fits the empirical data more accurately than the formerly used distributions, such as the generalized Gaussian and Laplacian, do. Authors also show that the bivariate alpha-stable distribution can capture the across scale dependencies of the contourlet coefficients. Motivated by the modeling results, a blind watermark detector in the contourlet domain is designed by using the univariate and bivariate alpha-stable distributions. It is shown that the detectors based on both of these distributions provide higher detection rates than that based on the generalized Gaussian distribution does. However, a watermark detector designed based on the alpha-stable distribution with a value of its parameter α other than 1 or 2 is computationally expensive because of the lack of a closed-form expression for the distribution in this case. Therefore, a watermark detector is designed based on the bivariate Cauchy member of the alpha-stable family for which $\alpha = 1$. The resulting design yields a significantly reduced-complexity detector and provides a performance that is much superior to that of the GG detector and very close to that of the detector corresponding to the best-fit alpha-stable distribution. The robustness of the proposed bivariate Cauchy detector against various kinds of attacks, such as noise, filtering, and compression, is studied and shown to be superior to that of the generalized Gaussian detector.

R. Eslami and H. Radha, [5] Most subsampled filter banks lack the feature of translation invariance, which is an important characteristic in denoising applications. In this paper, authors study and develop new methods to convert a general multichannel, multidimensional filter bank to a corresponding translation-invariant (TI) framework. In particular, authors propose a generalized algorithme agrave trous, which is an extension of the algorithme agrave trous introduced for 1-D wavelet transforms. Using the proposed algorithm, as well as incorporating modified versions of directional filter banks, authors construct the TI contourlet transform (TICT). To reduce the high redundancy and complexity of the TICT, authors also introduce semi-translation-invariant contourlet transform (STICT). Then, authors employ an adapted bivariate shrinkage scheme to the STICT to achieve an efficient image denoising approach. Our experimental results demonstrate the benefits and potential of the proposed denoising approach. Complexity analysis and efficient realization of the proposed TI schemes are also presented.

Table 1: Summary of Literature of Survey

SR. NO.	TITLE	AUTHORS	YEAR	METHODOLOGY
1	Contourlet domain image denoising based on the Bessel k-form distribution	H. Sadreazami, M. O. Ahmad and M. N. S. Swamy	2015	The contourlet coefficients of images are modeled by using the Bessel k-form prior.
2	Contourlet domain image denoising using normal inverse gaussian distribution	H. Sadreazami, M. O. Ahmad and M. N. S. Swamy	2014	A Bayesian maximum a posteriori estimator is developed utilizing the proposed distribution.
3	A Study of Multiplicative Watermark Detection in the Contourlet Domain Using Alpha-Stable Distributions	H. Sadreazami, M. O. Ahmad and M. N. S. Swamy	Oct. 2014	A novel multiplicative watermarking scheme in the contourlet domain.
4	Image denoising based on the symmetric normal inverse Gaussian model and non-subsampled contourlet transform	Y. Zhou and J. Wang	Nov. 2012	An adaptive image denoising method is proposed based on the symmetric normal inverse Gaussian (SNIG) model and the non-subsampled contourlet transform (NSCT).
5	Translation-Invariant Contourlet Transform and Its Application to Image Denoising	R. Eslami and H. Radha	Nov. 2006	Proposed a generalized algorithme agrave trous, which is an extension of the algorithme agrave trous introduced for 1-D wavelet transforms.
6	Spatially adaptive wavelet thresholding with context modeling for image denoising	S. G. Chang, Bin Yu and M. Vetterli	Sep 2000	Proposed a spatially adaptive wavelet thresholding method based on context modeling, a common technique used in image compression to adapt the coder to changing image characteristics.
7	Wavelet-based statistical signal processing using hidden Markov models	M. S. Crouse, R. D. Nowak and R. G. Baraniuk	Apr 1998	A new framework for statistical signal processing based on wavelet-domain hidden Markov models (HMMs).

S. G. Chang, Bin Yu and M. Vetterli, [6] The method of wavelet thresholding for removing noise, or denoising, has been researched extensively due to its effectiveness and simplicity. Much of the literature has focused on developing the best uniform threshold or best basis selection. Such adaptivity can improve the wavelet thresholding performance because it allows additional local information of the image (such as the identification of smooth or edge regions) to be incorporated into the algorithm. This work proposes a spatially adaptive wavelet thresholding method based on context modeling, a common technique used in image compression to adapt the coder to changing image characteristics. Each wavelet coefficient is modeled as a random variable of a generalized Gaussian distribution with an unknown parameter. Context modeling is used to estimate the parameter for each coefficient, which is then used to adapt the thresholding strategy. This spatially adaptive thresholding is extended to the overcomplete wavelet expansion, which yields better results than the orthogonal transform. Experimental results show that spatially adaptive wavelet thresholding yields significantly superior image quality and lower MSE than the best uniform thresholding with the original image assumed known.

M. S. Crouse, R. D. Nowak and R. G. Baraniuk, [7] Wavelet-based statistical signal processing techniques such as denoising and detection typically model the wavelet coefficients as independent or jointly Gaussian. These models are unrealistic for many real-world signals. Authors develop a new framework for statistical signal processing based on wavelet-domain hidden Markov models (HMMs) that concisely models the statistical dependencies and non-Gaussian statistics encountered in real-world signals. Wavelet-domain HMMs are designed with the intrinsic properties of the wavelet transform in mind and provide powerful, yet tractable, probabilistic signal models. Efficient expectation maximization algorithms are developed for fitting the HMMs to observational signal data. The new framework is suitable for a wide range of applications, including signal estimation, detection, classification, prediction, and even synthesis. To demonstrate the utility of wavelet-domain HMMs, authors develop novel algorithms for signal denoising, classification, and detection.

IV. PROBLEM IDENTIFICATION

Authors have developed a statistical model for the contourlet coefficients using the Bessel k-form distribution that can capture their heavy-tailed property. To estimate the noise-free coefficients, the noisy image is decomposed into various scales. A Bayesian estimator has been developed based on the Bessel k-form prior to remove noise from all the detail sub-bands. Previous results have been carried out to compare the performance of the proposed denoising method with that provided by some of the existing methods. The simulation results have shown that the proposed scheme performs other existing methods in terms of the PSNR values and provides denoised images with higher visual quality. In order to improve the system performance contourlet domain image denoising method has been proposed.

V. CONCLUSION

In this review paper the various image denoising methods have been analyzed. Whereas the Multiscale image analysis is known to be useful and indispensable to the field of image processing. Depending on the requirements of an application, a variety of multiscale and multi-resolution transforms have been used. Signals can be effectively projected using these transforms. The wavelet transform is by far the most prevalent transformation in signal processing offering a multiscale and multi-resolution signal representation.

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