A Literature Survey on Image Denoising Techniques

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Abstract- Image noise reduction, or denoising, is an active area of research, although many of the techniques cited in the literature mainly target additive white noise. Thorough the review and evaluation of state-of-the-art denoising methods, it was found that the representation of images is substantially important for the denoising technique. At the same time, an improvement on one of the nonlocal denoising method was proposed, which improves the representation of images by the integration of Gaussian blur, clustering and Rotationally Invariant Block Matching. In this review work the successful application of sparse coding in compressive sensing, the image self-similarity by using a sparse representation based on wavelet coefficients in a nonlocal and hierarchical way, which generates competitive results compared to the state-of-the-art denoising algorithms. Another adaptive local filter would be proposed for efficient image denoising.

Keywords-- Image Denoising, Wavelet Transform.

I. INTRODUCTION

A very vast portion of digital image processing is concerned with image de-noising. This includes research in algorithm and routine goal oriented image Processing. Image restoration is the removal or reduction of degraded images that are Incurred while the image is being obtained. Degradation comes from blurring as well as noise due to various sources. Blurring is a form of bandwidth reduction in the image caused by the imperfect image formation process like relative motion between the camera & the object or by an optical system which is out of the focus. When aerial photographs are taken for remote sensing purposes, atmospheric turbulence introduces blurs, optical system aberration and relative motion between camera and the ground. With these blurring effects, the recorded image can also be corrupted by noises. A noise can be 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 film, lenses, digitizer, etc. contribute to the degradation. Image de-noising is often used in the field of photography or publishing where an image is somehow degraded but it needs to be improved before it can be printed. For this type of application we need to know about the degradation process in order to design a model for it.

When a model for the degradation process is designed, the inverse process can be applied to the image to de-noise it back to its original form. It is the type of image de-noise often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to reduce distortion in the optical system of a telescope. Image de-noising finds applications in fields such as astronomy where the resolution limitations are high, in medical imaging where the physical requirements for high quality imaging are needed for analyzing the images of unique events and in the forensic science where potentially useful photographic information is sometimes of extremely bad quality.

Fig. 1. Shows the images with noises

Digital images are 2-D matrices in image processing and important task is to adjust values of these matrices in order to get clear features of images. The adjusting of values obeys a certain mathematical model. The main challenge is to build suitable mathematical models for practical requirements. Taking image de-noising example many mathematical models are based on a frequency partition of the image, where components having high frequency are interpreted as noise which have to be removed while those with low frequency can be seen as features to be remained. Curve-lets can be seen as an effective model that not only considers a multi scale time-frequency local-partition but also makes use of the direction of features.
Applications of wavelets are increasingly being used in scientific and engineering fields; traditional wavelets do well only at representing point singularities, as they ignore the geometric properties of structures and do not exploit the regularity of edges. Thus, de-noising, wavelet based compression or structure extraction become computationally inefficient for geometric features with line and surface singularities. For ex, when we download compressed image or video, we mostly find a mosaic phenomenon. The mosaic phenomenon comes from the poor ability of wavelets to handle line singularities. In fluid mechanics, discrete wavelet thresholding mostly leads to oscillations along edges of the coherent eddies, and to the deterioration of the vortex tube structures, which later can cause an unphysical leak of energy into neighboring scales producing an artificial “cascade” of energy.

II. ADDITIVE AND MULTIPlicative NOISES

Noise is undesired information that degrades the image. In the image de-noising process, information of the type of noise present in the original image plays a significant role. Mostly images can be corrupted with noise modeled with either a uniform, Gaussian, or salt and pepper distribution. Another type of noise is a speckle noise which is multiplicative in nature. Noise is present in image either in an additive or multiplicative form.

Rule for additive noise

\[ w(x, y) = s(x, y) + n(x, y), \ldots \ldots \ldots \ldots \ldots (1) \]

Rule for multiplicative noise

\[ w(x, y) = s(x, y) \times n(x, y), \ldots \ldots \ldots \ldots \ldots (2) \]

Where \((x, y)\) is original signal, \(n(x, y)\) is the noise introduced into the signal to produce a noisy image \(w(x, y)\), and \((x, y)\) is the pixel location. The above image algebra is done at pixel level. Image addition also has applications in image morphing. Image multiplication means the brightness of the image is varied.

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

III. DEENOISING METHODS

A. Discrete Wavelet Transform

Wavelets are the mathematical functions which analyze data according to the scale or resolution. They help in studying a signal in different windows or in different resolutions.

For example, if the signal is viewed in the large window, gross feature can be noticed, and if viewed in a small window, only the small features can be noticed. The wavelets provide some advantages over Fourier transforms. For instance, they do a great job in approximating signals with sharp spikes and signals having discontinuities. Wavelets can also model music, speech, video and non-stationary stochastic signals. The wavelets can be used in applications such as turbulence, image compression, human vision, earthquake prediction, etc.

The term “wavelets” is refered to a set of orthonormal basis functions generated by translation and dilation of scaling function \(\varphi\) and a mother wavelet \(\psi\). A finite scale multi resolution representation of a discrete function is called as a discrete wavelet transform. DWT is a fast linear operation on the data vector, whose length is an integer power of 2. This transform is orthogonal and invertible where the inverse transform expressed as the matrix is the transpose of the transform matrix. The wavelet basis or function, unlike sines and cosines in Fourier transform, is localized in space. Similar to sines and cosines the individual wavelet functions are localized in frequency.

The orthonormal basis or wavelet basis is defined as

\[ \psi_{(j,k)}(x) = 2^{j/2} \psi(2^j x - k) \]

The scaling function is given as

\[ \varphi_{(j,k)}(x) = 2^{j/2} \varphi(2^j x - k) \]

Where \(\psi\) is the wavelet function and \(j\) and \(k\) are integers that scale and dilate the wavelet function. Factor ‘\(j\)’ in Equations is called as the scale index, which indicates the width of the wavelet. The location index \(k\) provides the position. The wavelet function is dilated by powers of two and is translated by the integer \(k\). In terms of the wavelet coefficients, the wavelet equation is

\[ \psi(x) = \sum_{k} g_k \sqrt{2} \varphi(2x - k) \]

where \(g_0, g_1, g_2, \ldots\) are high pass wavelet coefficients. The scaling equation in terms of scaling coefficients as given below

\[ \varphi(x) = \sum_{k} h_k \sqrt{2} \varphi(2x - k) \]

The function \(\varphi(x)\) is the scaling function and the coefficients \(h_0, h_1, \ldots\) are low pass scaling coefficients. The wavelet and scaling coefficients are related by the quadrature mirror relationship, which is
Where \( N \) is the number of vanishing moments.

B. Wavelet Thresholding

The term wavelet thresholding is defined as decomposition of the data of image into wavelet coefficients, comparing the detailed coefficients having a given threshold value, and minimizing these coefficients close to zero to remove the effect of noise in the data. Then image is reconstructed from modified coefficients. This is also known as inverse discrete wavelet transform. At the time of thresholding, a wavelet coefficient is compared to the given threshold and is set to zero if its magnitude is less than the threshold otherwise, it is then retained or modified depending on the thresholding rule. Thresholding distinguishes between coefficients due to noise and the ones consisting of important signal information. The selection of a threshold is an important point of interest. It plays an important role in the removal of noise in the images because de-noising most frequently produces smoothed images, by reducing the sharpness of the image. Care should be taken to preserve the edges of the de-noised image. Various methods for wavelet thresholding exists, which rely on the choice of a threshold value. Typically used methods for image noise removal include Sureshrink, VisuShrink and BayesShrink. It is necessary to know about the two generic categories of thresholding. These are hard thresholding and soft thresholding. The hard-thresholding \( TH \) is given as

\[
TH = \begin{cases} 
  x & \text{for } |x| \geq t \\
  0 & \text{in all other region} 
\end{cases}
\]

Where \( t \) is the threshold value. A plot of \( TH \) is shown in Fig. 2 below.

Therefore, all coefficients whose magnitude is greater than the selected threshold value \( T \) remains same and the others with magnitudes smaller than \( t \) are set to zero. It creates a region around 0 where the coefficients are considered to be negligible.

Soft thresholding is that where the coefficients with greater than the threshold are shrunk towards zero after comparing them to the threshold value. It is defined as below

\[
T_s = \begin{cases} 
  \text{sign} (x)(|x| - t) & \text{for } |x| > t \\
  0 & \text{in all other region} 
\end{cases}
\]

![Fig. 3 Soft Thresholding](image)

Practically, it can be seen that the soft method is much better and yields more visually pleasant images. This is because the hard method is discontinuous and yields abrupt artifacts in the images recovered. Also, the soft method yields a smaller MSE (minimum mean squared error) compared to hard form of thresholding.

C. Multi Resolution Bilateral Filter Framework

Image noise is not necessarily white and may have different spatial frequency (fine-grain and coarse-grain) characteristics. Multi resolution analysis has been proven to be an important tool for eliminating noise in signals; it is possible to distinguish between noise and image information better at one resolution level than another. To put the bilateral filter in a multi resolution framework: Referring to Fig. 4, a signal is decomposed into its frequency sub-bands with wavelet decomposition.
As the signal is reconstructed back, bilateral filtering is applied to the approximation sub-bands. Unlike the standard single-level bilateral filtering, this multi resolution bilateral filtering has the potential of eliminating low-frequency noise components. (This will become evident in our experiments with real data.) Bilateral filtering works in approximation sub-bands; in addition, it is possible to apply wavelet thresholding to the detail sub-bands, where some noise components can be identified and removed effectively. This new image denoising framework combines bilateral filtering and wavelet thresholding.

IV. LITERATURE REVIEW

Donoho and Johnstone [6][7] provided an ideal spatial adaptive wavelet shrinkage. With ideal spatial adaptation, they described a new principle for spatially-adaptive estimation: selective wavelet reconstruction. It showed that variable-knot spline fits and piecewise-polynomial fits, when equipped with an oracle to select the knots, are not dramatically more powerful than selective wavelet reconstruction with an oracle. Then they developed a practical spatially adaptive method, Sure Shrink[7], which works by shrinkage of empirical wavelet coefficients. A new inequality in multivariate normal decision theory which they called the oracle inequality showed that attained performance differs from ideal performance.

Chang and Vetterli [8] proposed an adaptive, data-driven threshold for image denoising using the wavelet soft-thresholding. The threshold is derived in a Bayesian framework, and the prior used on the wavelet coefficients is the generalized Gaussian distribution (GGD) widely used in image processing applications. The proposed threshold is closed-form and adaptive to each sub-band. This method, so called BayesShrink [8], outperforms Donoho and Johnstone’s SureShrink [7] most of the time.

Since wavelet coefficients of real images have significant dependencies, Sendur et al. [9] considered the dependencies between the coefficients and their parents in the detail coefficients part. For this purpose, the non-Gaussian bivariate distributions are proposed, and corresponding nonlinear threshold functions are derived from the models using Bayesian estimation theory. The new shrinkage functions do not assume the independence of wavelet coefficients. However, the performance of this method is not very well.

Pezurica [10] et al. developed three wavelet domain denoising methods for sub-band adaptive, spatially adaptive and multi-valued image denoising. The core of his approach is the estimation of the probability that a given coefficient contains a significant noise-free component, which is called “signal of interest.”

In this respect, he analyzed cases where the probability of signal presence is I) fixed per sub-band, II) conditioned on a local spatial context, and III) conditioned on information from multiple image bands. All the probabilities are estimated assuming a generalized Laplacian prior for noise-free sub-band data and additive white Gaussian noise. His sub-band adaptive shrinkage function outperforms

Bayesian thresholding approaches in terms of Mean-Squared Error. Portilla [11] et al. developed a model for neighborhoods of oriented pyramid coefficients based on a Gaussian scale mixture: the product of a Gaussian random vector, and an independent hidden random scalar multiplier. This model, called BLS-GSM, can account for both marginal and pair-wise joint distributions of wavelet coefficients. Then he showed a local denoising solution as a Bayesian least squares estimator, and demonstrated the performance of this method on images corrupted by simulated additive white Gaussian noise of known variance. Portilla’s methods.

One of the best wavelet thresholding methods recently is the SureShrink based on the inter-scale orthonormal wavelet transform. Instead of postulating a statistical model for the wavelet coefficients, Luisier et al. [12] directly parameterized the denoising process as a sum of elementary nonlinear process with unknown weights. Then minimize an estimate of the mean square error between the clean image and the denoised one. He use the statistically unbiased, MSE estimate Stein’s unbiased risk estimate which depends on the noisy image alone, not on the clean one. Like the MSE, this estimate is quadratic in the unknown weights, and its minimization amounts to solving a linear system of equations. The existence of this a priori estimate makes it unnecessary to devise a specific statistical model for the wavelet coefficients. Instead, and contrary to the custom in the literature, these coefficients are not considered random anymore.

V. CONCLUSION

The noise may come from a noise source present in the vicinity of image capturing location or may be introduced due to imperfection inherent in the image capturing devices like cameras. For example, lenses may be misaligned, focal length may be weak, scattering and other adverse conditions may be present in the atmosphere, etc. This makes careful study of noise and noise approximation an essential ingredient of image denoising. This leads to selection of proper noise model for image processing system.
In this review work we have studied and analyzed the research study by considering methods based on machine learning to be the best adaptive representations for natural images. We have analyzed that the better results than conventional representation models for the tasks of image denoising and deblurring would be achieved.

REFERENCES


