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A COMPARITIVE STUDY OF IMAGE DENOISING TECHNIQUES

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ABSTRACT

Noise reduction from images is one of the most important challenge in digital image processing. Impulsive noise is one such noise, which may damage images during their acquirement or transmittance or storage etc. Removing noise from any refined image is very important noise should be removed in such a way that important information of image should be preserved. Noise reducing from the original signal is still a difficult problem for researchers. Image noise is random change of brightness or colour information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and irrelevant information. There have been multiple published algorithms and each approach has its assumptions, advantages, and boundaries. This paper provides a review of some significant work in the area of image denoising.

Keywords:Denoising Techniques; Gaussian Noise; Image Noise;Salt and Pepper Noise;Transform Domain; Wavelet.

I. INTRODUCTION

Digital images plays an important role in day to day life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in the areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally infected by noise. Defective instruments, difficulty with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. In addition, 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. It is necessary to apply an efficient denoising technique to balance for such data corruption [Motwani et al., 1]. Digital images may be infected by different sources of noise. Noise may be generated due to defective instruments used in image processing, problems with the data acquiring process, and interference, all of which can degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression also. Different types of noises are introduced by different noise sources like dark current noise is due to the thermally generated electrons at sensor sites. It is proportional to the exposure time and highly dependent on the sensor temperature. Shot noise, which has the characteristics of Poisson distribution, is due to the quantum uncertainty in photoelectron generation. Amplifier noise and quantization noise occur during the conversion of number of electrons to pixel intensities [Sudipta Roy et al., 2].

There are various methods to help renew an image from noisy damages. Selecting the appropriate method plays a major role in getting the desired image. The denoising performing tend to be problem specific. For example, a method that is used to denoise satellite images may not be suitable for denoising medical images. In order to compute the performance of the various denoising algorithms, a high quality image is taken and some known noise is added to it. This would then be given as input to the denoising algorithm, which produces an image close to the original high quality image. In case of image denoising methods, the characteristics of the degrading system and the noises are assumed to be known in advance. The image s(x,y) is blurred by a linear operation and noise n(x,y) is added to form the degraded image w(x,y). This is convolved with the restoration procedure g(x,y) to produce the restored image z(x,y).

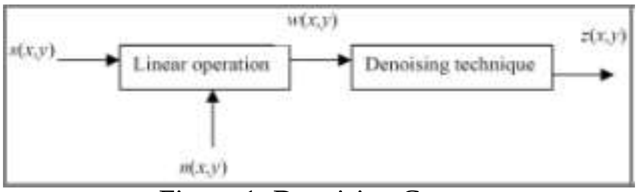

Figure 1: Denoising Concept

The “Linear operation” shown in Figure 1.1 is the addition or multiplication of the noise n(x,y) to the signal s(x,y). Once the corrupted image w(x,y) is obtained, it is subjected to the denoising technique to get the denoised image z(x,y). The point of focus in this thesis is comparing and contrasting several “denoising techniques” (Figure 1).

1.1. Noise types

Regular images are corrupted with additive noises modelled with either a Gaussian, uniform, or salt and pepper distribution. Another representative 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,

$$W(x,y) = s(x,y) + n(x,y) \qquad (1)$$

While the multiplicative noise satisfies, W(x,y) = s(x,y) x n(x,y) (2)

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 [Scott E Umbaugh, 15]. By image multiplication, we mean the brightness of the image is different.

1.1.1. 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 distribution, which has a bell shaped probability distribution function. Graphically, it is represented as shown in Figure 2.

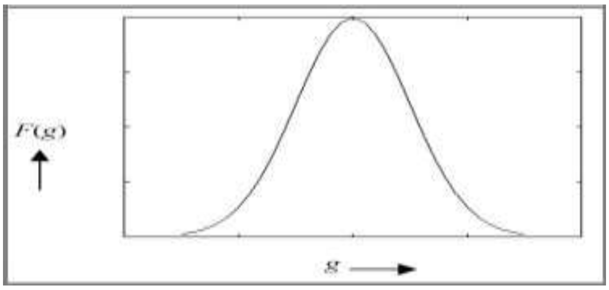

Figure 2: Gaussian Distribution

1.1.2. Salt and Pepper Noise

Salt and pepper noise [Scott E Umbaugh, 15] is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, a and b. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged. For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. The salt and pepper noise is generally caused by faulty of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. The probability density function for this type of noise is shown in Figure 3.Salt and pepper noise with a variance of 0.05 is shown in Figure 4.

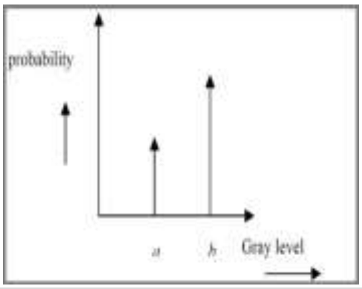

Figure 3: PDF for Salt and Pepper Noise

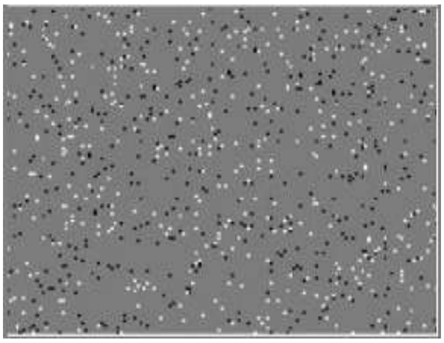

Figure 4: Salt and Pepper Noise

1.1.3. Brownian Noise

Brownian noise [16] comes under the category of fractal or 1/f noises. The mathematical model for 1/f noise is fractional Brownian motion. Fractal Brownian motion is a non-stationary stochastic process that follows a normal distribution. Brownian noise is a special case of 1/f noise. It is obtained by integrating white noise. It can be graphically represented as shown in Figure 5. On an image, Brownian noise would look like Figure 6, which is developed from Fraclab [Jacques LévyVéhel, 17].

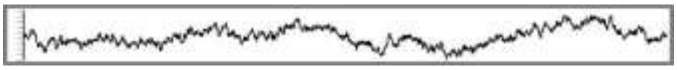

Figure 5: Brownian Noise Distribution

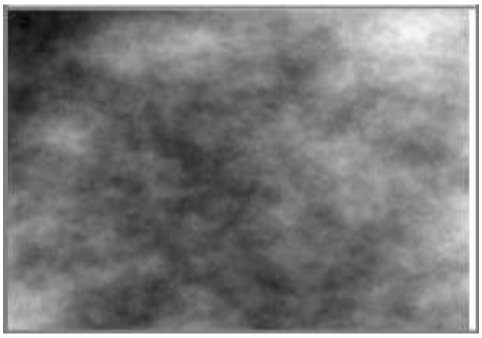

Figure 6: Brownian Noise

1.2. Classification of Denoising Techniques

There are two basic formulation to image denoising, spatial filtering methods and transform domain filtering methods.

1.2.1.Spatial Filtering

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

A. Non Linear Filter

With non-linear filters, the noise is removed without any attempts to clearly 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 amount 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 [Yang et al., 18], rank conditioned rank selection [Hardie & Barner, 19], and relaxed median [Ben Hamza et al., 20] have been developed to overcome this drawback.

B. Median Filter

Like the mean filter, the median filter considers each pixel in the image in turn and looks at its close neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighbouring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighbourhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighbourhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.)

C. Weighted Median Filter

The basic idea is to give weight to the each pixel. Every pixel is given a weight. This weight is multiply with pixel. According to this weight the pixels are sort into ascending order, and then find the median value from the sorted list. This value is replaced with center value.

D. Mean Filter

The idea of mean filtering is simply to replace each pixel value in an image with the mean (`average') value of its neighbours, including itself. This has the effect of eliminating pixel values which are unreliable of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean. Often a 3×3 square kernel is used, although larger kernels (e.g. 5×5 squares) can be used for more severe smoothing.

E. Weiner Filter

The Wiener filter purpose is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. It is based on a statistical approach. classic filters are designed for a desired frequency response. The Wiener filter approaches filtering from a different angle. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the LTI filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following: Assumption: signal and (additive) noise are stationary linear stochastic, processes with known spectral characteristics or known autocorrelation and cross correlation.

Requirement: the filter must be physically realizable, i.e. causal (this requirement can be dropped, resulting in a non-causal solution).

Performance criteria: minimum mean-square error.

1.2.2. Transform Domain Filtering

The transform domain filtering methods can be subdivided according to the choice of the basis functions. The basis functions can be further classified as data adaptive and non-adaptive. Non-adaptive transforms are discussed first since they are more popular.

A. Spatial-Frequency Filtering

Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods [Coifman & Donoho, 14] 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 adaptive filtering and non adaptive threshold filtering techniques.

C. Non Adaptive Threshold

VISU Shrink [Motwani et al., 1] 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.

D. Adaptive Threshold

SUREShrink [Motwani et al., 1] uses a hybrid of the universal threshold and the SURE [Stein‟ s Unbiased Risk Estimator] threshold and performs better than VISUShrink. BayesShrink [Simoncelli & Adelson, 21; Chipman et al., 22] minimizes the Bayes‟ Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold. BayesShrink outperforms SUREShrink most of the times. Cross Validation [Marteen Jansen, 23] replaces wavelet coefficient with the weighted average of neighborhood coefficients to minimize Generalized Cross Validation (GCV) function providing optimum threshold for every coefficient. The assumption that one can differentiate noise from the signal solely based on coefficient magnitudes is violated when noise levels are higher than signal magnitudes. Under this high noise circumstance, the spatial configuration of neighboring wavelet coefficients can play an important role in noise-signal classifications. Signals tend to form meaningful features (e.g. straight lines, curves), while noisy coefficients often spread randomly.

II.EVALUATION OF RESEARCH

Image Denoising has remained a fundamental problem in the field of image processing. Wavelets give a superior performance in image denoising due to properties such as sparsity and multiresolution structure. With Wavelet Transform gaining popularity in the last two decades various algorithms for denoising in wavelet domain were introduced. The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain. Although Donoho‟ s concept was not revolutionary, his methods did not require tracking or correlation of the wavelet maxima and minima across the different scales as proposed by Mallat & Hwang [11]. Thus, there was a renewed interest in wavelet based denoising techniques since Donoho [12] demonstrated a simple approach to a difficult problem. Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients. Data adaptive thresholds [Imola K. Fodor & Chandrika Kamath, 13] were introduced to achieve optimum value of threshold.

III. LITERATURE SURVEY

In 2009, Zuofeng Zhou et al., [3], Contourlet is a new effective signal representation tool in many image applications. In this paper, a contourlet-based image-denoising algorithm using adaptive windows which utilizes both the captured directional information by the contourlet transform and the intrinsic geometric structure information of the image is proposed. The adaptive window in each of the contourlet sub band is first fixed by autocorrelation function of contourlet coefficients' energy distribution, and then the local Wiener filtering is used to denoise the noisy image. Experiments show that the proposed algorithm achieves better performance than current subsampled contourlet based image denoising algorithms.

In 2012 Joachimiak et al., [4], "Multiview 3D video denoising in sliding 3D DCT domain". With the widespread interest in 3D technology are as such as displays, cameras, and processing, the 3D video is becoming widely available. Due to correlation between views in multiview 3D video at the same temporal location, it is possible to perform video processing operations more efficiently comparing to regular 2D video. so as to improve denoising performance for multiview video, we propose an algorithm based on denoising in 3D DCT domain, which is competitive in performance with state-of-art denoising algorithms and it is suitable for real-time implementation. The proposed algorithm searches for corresponding image patches in temporal and inter-view directions, selects 8 patches with lowest dissimilarity measure, and performs denoising in 3D DCT domain. The novel inter-view image patch search method brings up to 1.62dB gain in terms of average luma Peak Signal-to-Noise Ratio (PSNR), with average gain 0.6-0.8 dB depending on the amount of noise present in test sequences.

In 2013, Kaimal et al., [5], "A modified anti-forensic technique for removing detectable traces from digital images". The increasing magnetism and trust on digital photography has givenrise to new acceptability issues in the field of image forensics. There are many advantages to using digital images. Digital cameras produce immediate images, allowing the photographer to outlook the images and immediately decide whether the photographs are sufficient without the delay of waiting for the film and prints to be processed. It does not require external developing or reproduction. Additionally, digital images are easily stored. No conventional "original image" is prepared here like traditional camera. Thus, when forensic researchers analyze the images they don't have access to the original image to compare. Fraud by conventional photograph is relatively difficult, requiring technical expertise. Whereas significant features of digital photography is the ease and the decreased cost in altering the image. Manipulation of digital images is simpler. With some fundamental software, a digitally recorded image can easily be edited. A number of techniques are available to verify the authenticity of images. But the fact is that number of image tampering is also increasing. For this purpose, they have to find the new anti-forensic techniques and solutions for them.

In 2013, Hagawa [6], "Using Extended Three-valued Increment Sign for a denoising model of high-frequency artifacts in JPEG images by estimation of specific frequency". Author presented a robust denoising model for high-frequency artifacts resulted by compressing images into JPEG. In this model, the authors used only simple evaluation value named Extended Three-valued Increment Sign (ETIS). ETIS represents the relationship of adjacent pixels, which one is brighter or almost the same. The authors estimated that ETIS difference between Compressed Image and Noise Image would be small except edge region. Then they figured out the sum of the squares of those differences and utilized it in noise estimation. Only quantization process cause the artifacts, then they optimized DCT coefficient matrix in non-linearly based on ETIS, and estimated high-frequency artifacts as an independent approach without smoothing process.

In 2013, Jin Xu et al., [7], “Monochromatic Noise Removal via Sparsity-Enabled Signal Decomposition Method”. Monochromatic noise always interferes with the interpretation of the seismic signals and degrades the quality of subsurface images obtained by further processes. Conventional methods suffer from several problems in detecting the monochromatic noise automatically, preserving seismic signals, etc. Based on their diverse morphologies, two waveform dictionaries are chosen to represent each component sparsely, and the separation process is promoted by the sparsity of both components in their corresponding representing dictionaries. Both synthetic and field-shot data are employed to illustrate the effectiveness of our method.

In 2013, Abramov et al., [8], “Prediction of filtering efficiency for DCT-based image denoising”. The task of calculation practical efficiency of filtering on the basis of the Discrete Cosine Transform (DCT) methods is considered. It is shown that it is possible to estimate the MSE values of images to be processed by means of calculation rather simple statistics of DCT coefficients. Besides, the quasi-optimal value of threshold parameter for DCT filtering methods can be easy evaluated as well. The results are presented for different additive Gaussian noise levels and a set of gray-scale test images.

In 2013, Padmagireeshan et al., [9], “Performance Analysis of Magnetic Resonance Image Denoising Using Contourlet Transform”. A medical image denoising algorithm using contourlet transform is proposed and the performance of the proposed method is analysed with the existing methods. Noise in magnetic resonance imaging has a Rician distribution and unlike AWGN noise, Rician noise is signal dependent. Separating signal from Rician noise is a tedious task. The proposed approaches were compared with other transform methods such as wavelet thresholding and block DCT. Hard, soft and semi-soft thresholding techniques are described and applied to test images with threshold estimators like universal threshold. The results are compared based on the parameters: PSNR and MSE. Numerical results show that the contour let transform can obtained higher PSNR than wavelet based and block DCT based denoising algorithms.

In 2013, Fedak & Nakonechny [10], “Image denoising based on optimized NLM algorithm”. Images and video are often coded using block based Discrete Cosine Transform (DCT) or Discrete Wavelet Transform (DWT) that cause a great deal of visual distortions. Non- Local Means (NLM) algorithm is chosen through comparing complexity and quality of different algorithms and is considered to be the better algorithm for artifacts reduction. as well, implementation of this algorithm is computationally intensive. In this note, improvements to the non-local means introduced are presented and very effective performance optimization approach is presented. This approach is based on additional memory usage for caching pixels distance in the image. We present the underlying framework and experimental results for video that is processed by NLM with different parameters.

IV. CONCLUSION

The goal of this paper is to present a survey of digital image deniosing approaches. As images are very important in each and every real wold fields so Image Denoising is an important pre task before further processing of image like segmentation, feature extraction, texture analysis etc. This survey shows the different type of noises that can corrupt the image and different type of filters which are used to recover the noisy image. Different filters show different results after filtering. Some filters degrade image quality and remove edges. Performance of denoising algorithms is measured using quantitative performance measures such as Peak Signal-to-Noise Ratio (PSNR), Signal-to-Noise Ratio (SNR) as well as in terms of visual quality of the images.

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