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Removing Image Gaussian Noise Using Riesz Wavelet Transform and SVM

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***Abstract*—*Image denoising is an important aspect of image processing. Image denoising is first step of most of image processing applications. There is only one goal of image denoising; to remove noise from images and provide best image in all possible ways. Noise gets added into images during acquisition, storage and transmission. This paper propose an image denoising technique which employs an SVR (Support Vector Regression), a machine learning technique on the noisy images, after performing wavelet transform on them. This work is intended towards removal of AWGN from grayscale images. Support Vector (SV) algorithm, used here is a supervised learning model and algorithm; it is used for classification and regression analysis. In this work, two dimensional Riesz wavelet transform is used to perform wavelet transform of noisy image, with its monogenic steering property it forms heart of proposed denoising algorithm. Wavelet transform is very popular in image denoising field. It forms the basis of almost all signal denoising algorithms; most of successful and famous image denoising algorithms are based on wavelet transform.*

***Keywords:*— *Image Denoising, Riesz Wavelet Transform. Support Vector Regression (SVR), Support Vector Machine (SVM), monogenic analysis.*

1. INTRODUCTION

Image denoising is simply the removal of noise from images. Due to the imperfection of image acquisition systems and transmission channels, images are often corrupted by noise. This degradation leads to a significant reduction of image quality and then makes more difficult to perform high-level vision tasks such as recognition, 3-D reconstruction, or scene interpretation. Image noise can be defined as random (not present in the object imaged) variation of brightness or color information in images.

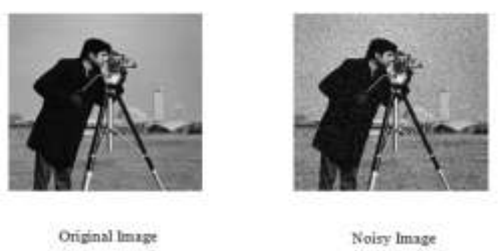

Figure 1: Depicting noise in images

In most cases, this corruption is commonly modeled by a zero-mean additive white Gaussian random noise leading to the following additive degradation model

$$f(x,y)=f(x,y)+n(x,y) \quad (1)$$

Image de-Noising is prime requirement in many fields for example in defense applications, Satellite images, ATC, Medical Imagery etc. Noise in the images is classified mostly depending on their probability density function (pdf) and sometimes depending on the source of noise. Following are the types of noise that degrade the images [13]:

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).

Salt-and-pepper noise - Impulse noise is sometimes called salt-and-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.

Poisson noise - The image acquisition devices are photon counters. Then, the distribution of photon count is usually modeled as Poisson. This noise due to abnormal photon counts is called Poisson noise or Poisson counting noise.

Quantization noise - The noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise.

Section 2 discuss existing techniques in field of image denoising, section 3 talks about wavelet transform with section 4 presenting information about SVR, section 5 mentions proposed method with section 6 about results and conclusion.

2. EXISTING METHODOLOGIES

Image denoising falls under the category of image enhancement, extensive work is done in the field, previously and is still in progress. The reason for such extensive research is that there is no standard way to remove noise from the images, if there is some promising research providing good results, the next could be better. This section provides a basic understanding of existing research in the field of image denoising.

There are two basic approaches to image denoising; it can be done in spatial as well as in frequency domain, spatial domain is a traditional way to remove noise from image data by employing spatial filters. Spatial filters can be further classified into non-linear and linear filters, wiener filter is example of linear method and median filtering is an example of non linear filtering, more on spatial filtering can be found in [13]. Spatial filters tend to cause blurring in the denoised image.

In frequency domain the images are transformed first and then modification on wavelet coefficients takes place. This estimation of clean coefficients is done by one of following method, which includes thresholding, shrinkage and statistical approaches. By thresholding the low frequency signals, most of which is noise, gets removed.

Wavelet transforms have become a very powerful tool in the area of image denoising. Although new transforms like curvelet and ridgelet transforms are developed this provides some advantages in one sense or other.

Wavelet transform is key ingredient in most of image denoising algorithm. The reason behind wavelet's popularity is that it provides an appropriate basis for separating noisy signal from the image signal and its properties such as sparsity and multiresolution structure as shown by Mallat[11]. The motivation is that as the wavelet transform is good at energy compaction, the small coefficient are more likely due to noise and large coefficient due to important signal features. These small coefficients can be thresholded without affecting the significant features of the image. A good review of thresholding in wavelet domain is provided in [10].

Donoho's Wavelet based thresholding approach was published in 1995 [12], and since then there was a surge in the denoising papers being published. Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients[10]. Data adaptive thresholds [9,14] were introduced to achieve optimum value of threshold. Later efforts found that substantial improvements in perceptual quality could be obtained by translation invariant methods based on thresholding of an Undecimated Wavelet Transform [15,7]. These thresholding techniques were applied to the non-orthogonal wavelet coefficients to reduce artifacts. Multiwavelets were also used to achieve similar results.

Probabilistic models using the statistical properties of the wavelet coefficient seemed to outperform the thresholding techniques and gained ground. Recently, much effort has been devoted to Bayesian denoising in Wavelet domain. Hidden Markov Models and Gaussian Scale Mixtures have also become popular. Tree Structures ordering the wavelet coefficients based on their magnitude, scale and spatial location have been researched. Data adaptive transforms such as Independent Component Analysis (ICA) have been explored for sparse shrinkage. The trend continues to focus on using different statistical models to model the statistical properties of the wavelet coefficients and its neighbors.

SVR is relatively newer player in field of image denoising. SVM offers various advantages over other methods like it does not use a particular parametric image model to be fitted. Its solution may be found for complex noise sources even without knowing the functional form of the noise PDF and it is capable to take into account the relations among wavelet coefficients of natural images. Laparra et.al [1, 2] describes a method to take into account the relations among wavelet coefficients in natural images for denoising, they used support vector machines (SVM) to learn these relations. They also provide details of other denoising approaches using SVM.

3. THEORY OF WAVELET TRANSFORM

Wavelet transform is key ingredient in most of image denoising algorithms. The reason behind wavelet's popularity is that it provides an appropriate basis for separating noisy signal from the image signal and its properties such as sparsity and multiresolution structure as shown by Mallat [20]. Wavelet transform is good at energy compaction so less energy coefficients are due to noise and can be separated from image coefficients. We will here start by giving brief description of wavelet transform and then we will move to discussion of Riesz Wavelet Transform used in proposed work.

In signal processing Fourier Transform has a very special place as an analysis tool, but in Fourier expansion only frequency resolution is obtained it does not provide time resolution. Short Time Fourier transform (STFT) was developed to overcome above mentioned disadvantage, but it provides constant resolution at all frequency. As a matter of fact, STFT at any time can provide either good frequency resolution or good time resolution but not both. Thus, Wavelet transform emerged as a tool for both time and frequency analysis of signal. A wave is describe as an oscillating function of time or space, in contrast to it, a wavelet is a small wave whose energy is concentrated or localized in time. The Fourier analysis is thus based on a sinusoidal wave. The Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions.

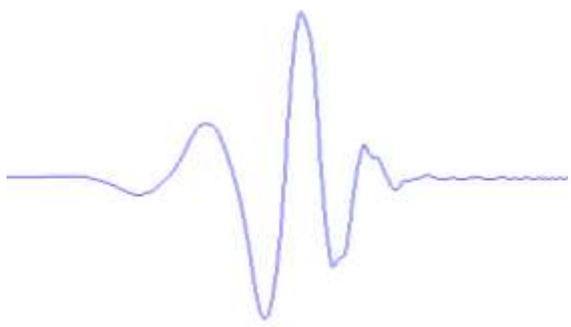

Figure 2: Wavelet: a localized wave

Wavelets are the functions generated from single function called as basis function or mother wavelet [21]. Following equation provides the wavelet transform of the function f(t) which is to be analyzed.

$$W(s, \tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-\tau}{s}\right)dt$$

The function $\psi(\tau)$ is the mother wavelet. It is the, dilations (expansions) or scaling and translation (shifting) of the mother wavelet which analyses the signal. The parameter s is called as scale parameter it is responsible for expansion or dilation of mother wavelet. The parameter τ is called as translation parameter it is responsible for shifting the mother wavelet.

Thus, the f(t) maps a one-dimensional function f(t) to a function W (s, τ) of two continuous real variables s (dilation) and τ (translation). The function W (s, τ) is called as Continuous Wavelet Transform of f(t). The most prominent difference between Wavelet and Fourier or any other transform is that a specific function is for wavelet basis is not defined. Thus, there are varieties of functions which can be used as wavelet basis depending on need.

With use of digital computing, existence of all signals is in digital form therefore we need a discrete transform for such signals. When input signal f(t) as well as dilation and translation parameter (s and τ respectively) are in discrete form the wavelet transform is called as Discrete Wavelet Transform (DWT).

Discrete Wavelet Transform representation of any signal is done by using filter banks, which is a key to multiresolution analysis of signal [22]. Let us assume there is a signal x(n) and figure 3 shows a analysis filter bank. The input signal x(n) passes through two paths the output of both paths are the decimated version of input. The decimation is done by factor of 2. The upper path consists of filter H0 which is a low pass filter and similarly H1 is a high path filter. If we assume x(n) with N samples, which is an even number, then output consists of N/2 samples. The process discussed above is called as wavelet decomposition as shown in figure 3.

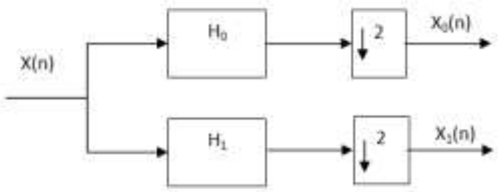

Figure 3 : Analysis Filterbank

In a Similar way we can create a synthesis filter bank, in this filter bank first stage is an upsampler of factor 2; hence, it doubles the number of samples of the input. If N/2 is the input, output of upsampler is N samples. Next stage is filtering by low pass filter G0 and high pass filter G1. The systhesis filtering is shown in figure 4.

Now, if output of analysis stage is applied at input to synthesis filter and certain filter criteria is met then the output of synthesis is identical to x(n) which was original input. Such condition is called as perfect reconstruction. One such case is obtained when h0(n) and g1(n) are unit impulse functions and rest are unit delay function.

Now, if filters are orthonormal and following criteria is met

g0(n) = (-l)nhl(n),

gl(n) = (-l)n+1h(n),

and

hl(n) = (-1)-nh0(k- n),

where, k is an integer delay then, the filters are known as quadrature mirror filters (QMF's). Biorthogonal filters also exists, the transform is not orthogonal in that case.

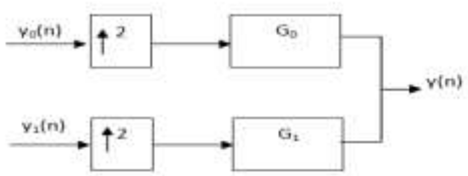

Figure 4: Synthesis Filterbank

As 1d signal is decomposed into low pas and high pass filter by using filterbanks, similar operation can be employed to images, which are actually 2d signals. The filtering can be done by filtering along rows first and then to columns or vice versa. Figure 5 shows how this operation can be performed on images; the filter shown is a two stage filter. In first stage the image is divided into two components low pass denoted by L and high pass denoted by H.

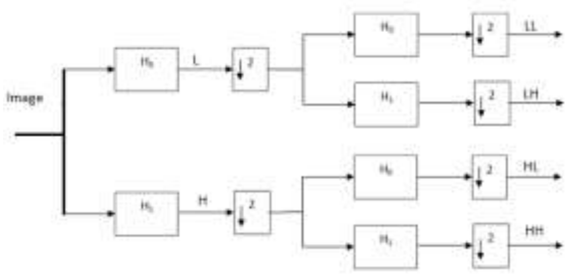

Figure 5: Two stage filtering

The output at first stage is again applied to similar filter now L is again divided into low pass and high pass component LL and LH. Similarly, the output H at first stage is again divided to give a low pass and high pass component denoted as HL and HH. These decomposition components are called as subbands.

Recursively applying above process will give us wavelet decomposition of images. Each stage of decomposition will result in three detailed component and 1 coarse component, which is again decomposed to produce more subbands. By choosing a proper wavelet family required wavelet image decomposition can be obtained. Figure 6 shows a 2 stage decomposition scheme for images.

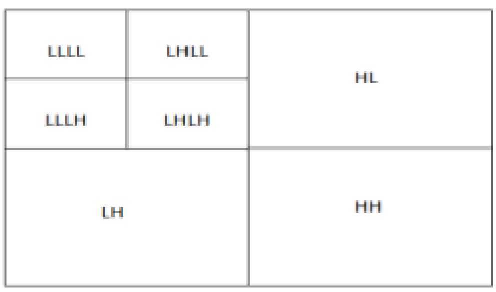

Figure 6: Two level wavelet decomposition of images

4. SUPPORT VECTOR MACHINES

Support vector machines (SVM)[8,16] have been applied in classification and function estimation problems. SVM separate training data into two classes. The goal of the SVM is to find the hyper-plane that maximizes the minimum distance between any data point as shown in following figure.

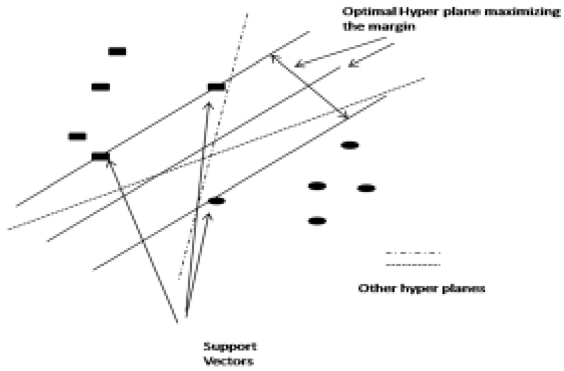

Figure 7: SVM concept

Now, given an input-output pair of N-dimensional vectors $\{x_i, y_i\}_{i=1}^{N}$ whereae x_i $\in R^n$ r $\{x_i, y_i\}_{i=1}^{N}$ the wavelet indices and $y_i \in \{-1, +1\}$ are the noisy wavelet coefficients, and a non-linear mapping Φ) x to a higher dimensional feature space, the SVM computes the weights *w* to obtain the estimation,

$$y(x)=w^T)\,\Phi\;x\;+b$$

minimizing the following regularized functional:

$$\frac{1}{2}\,w^T w + C\sum_{i=1}^{N}\xi_i$$

Subject to

$$y_i(w^T\Phi(x_i) + b) \geq 1 - \xi_i$$

Where ξ_i are the magnitude of the deviations of the estimated signal from the observed noisy data. Parameter *C* tunes the trade-off between fitting the model to the observed noisy data and keeping model weights ||*w*|| small.

Explicitly working with the non-linearity) $\Phi \quad x$ is removed as formulation can be expressed in the form of dot products of the mapping functions called kernels. Several types of kernels, such as linear, polynomial, splines, RBF, and MLP, can be used within the SVM. Kernel maps data to higher dimension space and provide us with dot product. In higher dimension space non linear separation is mapped to form a linear case.

SVM's are solved by quadratic programming which could be tricky sometimes. The need for quadratic programming can be rectified by using least square method in which we are just required to solve linear equations. Such kind of SVM is said to be LS-SVM.

4. PROPOSED METHOD

The method proposed removes AWGN from 256 x 256 grayscale images. The proposed method is the implementation of algorithm by Laparra et al. [1, 2], using Riesz wavelet transform [3, 4]. Laparra et al. proposed a non parametric way which uses SVR to remove noise from the images. Following sections describes the algorithm and then implementation details are provided.

In wavelet domain actual image and noisy coefficient exhibit specific properties, it becomes key to separate noise from images. The image corrupted by Gaussian noise is transformed by using Riesz Wavelet Transform. The Riesz wavelet transform is rotation and shift invariant transform and it makes inherent relations in signal clearer as respect to orthogonal transforms [3, 23]. The support vector regression, regularization [1, 8] is used then, to estimate the values of noisy signal based on inherent relations of image coefficients. Support vector machines are used for classification and regression; it can classify between two classes of data and could estimate data in regression analysis. The properties shared by wavelet coefficient are not present in noisy coefficients thus SVR can differentiate between original image coefficients and noisy coefficients. Finally, wavelet reconstruction is done to get the clean image. Following figure shows the block diagram of proposed work.

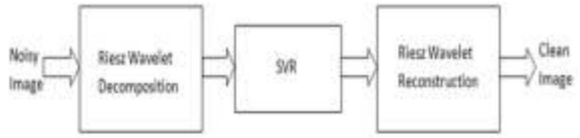

Figure 8: Proposed work

The proposed work performs monogenic steering [22] of noisy image. The Riesz wavelet transform are steerable transform, which means wavelets can be rotated to any orientation. The steering of the basis function is done to get maximum response [3]. Monogenic signal is 2d counterpart of 1d analytic signal developed by Felsberg et al [24]. Prior to monogenic steering, Riesz wavelet transformation of order 7 and 3 scales is calculated.

The monogenic analysis of image provides a point-wise estimation of the orientation, phase, etc for each scale of the wavelet transform. The localized phase angles obtained by monogenic analysis are employed to steer the wavelet decomposition.

SVR regularization is used to get clean image (denoised). The SVR uses mutual information Gaussian kernel. Adaptive SVR [1, 17] is used to approximate the signal, the term adaptive here specify that separate kernel is used for each order. The functioning of SVR depends on three parameters that are C which is penalization factor, ε which is insensitivity and kernel. The parameter, C_i and ε_i, changes with every scale and that in turn changes the kernel. There is one more parameter σ which is kernel width parameter.

5. RESULT AND CONCLUSION

This part discusses results of the proposed algorithm; results are also compared with existing algorithms. The performance metric used is SSIM. SSIM evaluates the image based on human perception; it is a widely used algorithm and is better than PSNR and RMSE, which are based on Euclidean distance. An image with high PSNR may look unpleasant to us whereas a better looking image has low PSNR; such discrepancy is removed using SSIM. Attached figure shows the snapshot of the system and figure 10 shows the output for Lena image with AWGN contamination of σ =20.

Figure 9: Output Snapshot

Figure 10: Output for Lena image σ =20

The performance of system is tested and compared with some other denoising algorithms. Standard 256 x 256 grayscale images of Lena, with different level of contamination (σ = 20, 25, 30) is denoised.

Table 1: SSIM for different level of contamination

Image	σ	Input	Output Image
Lena	20	0.42	0.86
Lena	25	0.34	0.83
Lena	30	0.29	0.79

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