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Image Denoising Using Riesz Wavelet Transform and SVR

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***Abstract* - This paper discusses an image denoising technique which employs an SVR (Support Vector Regression) machine learning technique after performing wavelet transform on the image. Image denoising is an important image processing step in itself and as a pre processing part of some other image processing tasks. The paper proposes an algorithm for removing AWGN from grayscale images. Support Vector (SV) algorithm used here is a supervised learning model and algorithm that analyze data and recognize patterns, used for classification and regression analysis. It is a state of art machine learning algorithm used in pattern and face recognition. SVM is getting popular in image denoising for classification as well as estimation of noisy wavelet coefficients. The wavelet transform forms the basis of almost all signal denoising algorithms, in this paper, 2d Riesz Wavelet transform is used to perform wavelet transform of noisy image, with its monogenic steering property it forms heart of proposed denoising algorithm.**

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

I. 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.

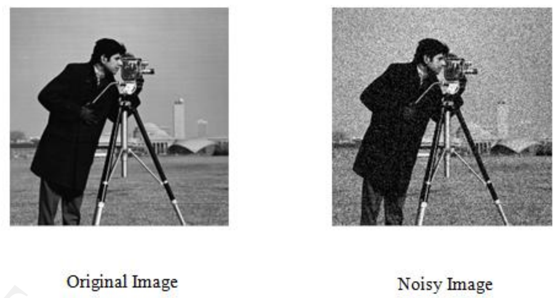


Figure 1: Depicting noise in images

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.

II. 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 which 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].

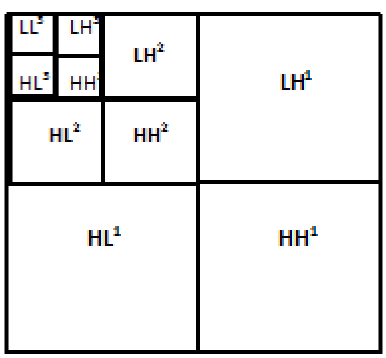
Donoho’s Wavelet based thresholding approach was published in 1995 [12], and since then there was a surge in the denoising papers being published. Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients[10]. Data adaptive thresholds [9,14] were introduced 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.

III. Theory of Wavelet Transform

The discrete wavelet transform (DWT) is identical to a hierarchical sub-band system where the sub- bands are logarithmically spaced in frequency and represent octave-band decomposition. By applying a two dimensional DWT to an image, the image is divided into four sub-bands, these four sub bands arise from convolving rows and columns with low-pass filter L and high-pass filter H and down sampling by two [10 ,11].



1,2,3………...Decomposition levels,

H……………….High frequency bands

L…..…………...Low frequency bands

Fig.2 Wavelet decomposition

This kind of two-dimensional DWT leads to a decomposition of approximation coefficients CAj at level j in four components: the approximation CAj+1 at level j + 1 and the details in three orientations: horizontal, vertical, and diagonal. Noise mainly dominates the detail coefficients in DWT, if we can set a reasonable threshold λ, we can drop all the noise contaminated detail coefficients to zero to remove noise from our images.

IV. 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.

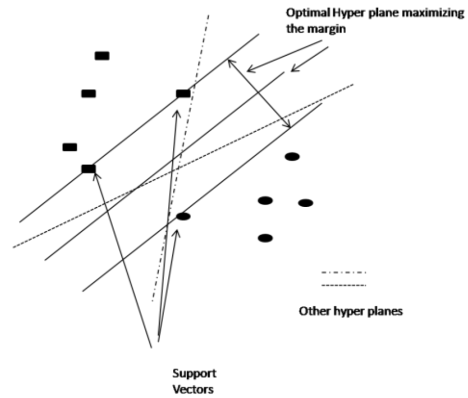


Fig. 3 SVM concept

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

$$y(x)=w^T \Phi(x) + b \quad (2)$$

minimizing the following regularized functional:

$$\frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \qquad (3)$$

Subject to

$$y_i(w^T \Phi(x_i) + b) \geq 1 - \xi_i \ (4)$$

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 $\Phi(x)$ 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.

V. Proposed Method

The method proposed applies 2d Riesz wavelet transform to noisy image. The Riesz transform is the natural multidimensional extension of the Hilbert transform [3,4]. The 2d Riesz wavelet transform is steerable pyramid wavelet transform. The steerable pyramid is a multi-orientation, multi-scale image decomposition which was developed by Simoncelli and others [5]. It is a wavelet-like representation whose analysis functions are dilated and rotated versions of a single directional wavelet. Steerability is defined as the property that the underlying wavelets can be rotated to any orientation by forming suitable linear combinations of a primary set of equiangular directional wavelet components. This provides a powerful mechanism for adapting the transform to the local characteristics of the image by steering the basis functions in the direction of maximal response. The monogenic steering property of Riesz transform is applied to noisy image with 8 orientation and 4 scales.

The resultant coefficients are then treated by support vector regression which estimates the noisy coefficients thus cleaning the image. The SVR [8] uses a mutual information Gaussian kernel as proposed by [2]. The parameters of SVR is selected on the basis of results obtained in [1,2,17,18]

The algorithm is implemented over MATLAB it uses Generalized Riesz-Wavelet Toolbox for Matlab [3]. SVR is implemented by IRWLS algorithm.

VI. Result and Conclusion

Following is the output of proposed algorithm for AWGN with SD 10 and 20 for very famous lena image. The performance parameter used is SSIM [19] i.e. structural similarity index which provide a meaningful measurement criteria for images. The SSIM is a well-known quality metric used to measure the similarity between two images. It was developed by Wang et al. [9], and is considered to be correlated with the quality perception of the human visual system (HVS). Instead of using traditional error summation methods, the SSIM is designed by modeling any image distortion as a combination of three factors that are loss of correlation, luminance distortion and contrast distortion. It provides a value between 0 and 1.

Fig. 4 Original Lenna image

Fig. 5a Noisy image with SD=10

Fig. 5b Denoised image using Riesz wavelets and SVR

Fig. 6a Noisy image with SD=20

Fig. 6b Denoised image using Riesz wavelets and SVR

Following table shows comparison of proposed algorithm with existing methods.

Table 1. SSIM comparison between existing algorithms for variance 400

Method	SSIM
HT	0.73
ST	0.71
BG	0.73
BL	0.72
GSM	0.85
SVM	0.81
Proposed Method	0.85

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