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An Efficient SVD Based Filtering For Image Denoising With Ridgelet Approach

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***Abstract*—** Images are often contaminated by noise during the processes of acquisition and transmission. One of the fundamental challenges in the field of image processing and computer vision is image denoising, where the underlying goal is to estimate the original image by suppressing noise from a noise-contaminated version of the image. There are various existing methods to denoise image. The important property of a good image denoising model is that it should completely remove noise as far as possible as well as preserve edges. Discrete Cosine Transform(DCT), Discrete Wavelet Transform(DWT) ,Singular Value Decomposition(SVD), Ridgelet transform etc are used for denoising. Because of the lack of sparsity, edges cannot be coded or restored effectively using DCT.Wavelet transform fails to provide an adequate sparse representation for image containing complex singularities. SVD provide low computational complexity. But it requires some more methods for solving large images. Ridgelet transform is able to compete with the wavelet transform in current era of image restoration but slightly inferior in homogenous region in non textured images. Proposed method combines SVD and Ridgelet transform .Experimental results demonstrate that the proposed method can effectively reduce noise and be competitive with the current state-of-the-art denoising algorithms in terms of both PSNR and subjective visual quality.

***Keywords*—** Image denoising, low-rank approximation, patch grouping, self-similarity, singular value decomposition, Ridgelet transform.

I. Introduction

Digital images play an important in research and technology. It is the most vital part in the field of medical science such as ultrasound imaging, X-ray imaging, Computer tomography and MRI. A very large portion of digital image processing includes image restoration. Image restoration is a method of removal or reduction of degradation that are incurred during the image capturing. Degradation comes from blurring as well as noise due to the electronic and photometric sources. Generally, denoising algorithms can be roughly classified into three categories: spatial domain methods, transform domain methods and hybrid methods.

Over the past several decades, image denoising has been extensively studied in the signal processing community, and numerous denoising techniques have been proposed in the literature.In 1995 David L. Donoho introduce De-noising by soft thresholding[1]. Owing to its rapidly increasing popularity over last few decades, the wavelet transform has become quite a standard tool in numerous research and application domains.

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In 2002 Jean-Luc Starck, Emmanuel J. Candès, and David L. Donoho introduced curvelet transform for image denoising[2]. Introduced a family of transforms—the ridgelet and curvelet transforms which had been proposed as alternatives to wavelet representation of image data. These methods provided exact reconstruction, stability against perturbations, ease of implementation, and low computational complexity. But it was found that the digital curvelet transform is nonorthogonal, quite redundant and as a consequence, the noisy coefficients are correlated and one should clearly design thresholding rules taking into account this dependency.

In 2003, Minh N. Do, *Member, IEEE, and Martin Vetterli, Fellow, IEEE* introduced finite ridgelet transformfor Image Representation[3]. The discrete ridgelet transform approach, with its built-in linear geometrical structure, provide a more direct way by simply thresholding significant ridgelet coefficients in denoising images with straight edges. ridgelets are very effective in representing objects with singularities along lines. . For complex images, where edges are mainly along curves and there are texture regions (which generate point discontinuities), the ridgelet transform was not optimal. Two-dimensional DCT[5] was introduced by Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian in 2007. the DCT has been successfully used as the key element in many compression and denoising applications. However, in presence of singularities or edges such near-optimality fails

In 2013 Shuyuan Yang,Wang Min, Linfang Zhao and Zhiyi Wang introduced image noise reduction via geometric multiscale ridgelet support vector transform anddictionary learning[6] . They proposed a new ridgelet support vector machine (RSVM) for image noise reduction. Multiscale ridgelet support vector filter (MRSVF) is first deduced from RSVM, to produce a multiscale, multidirection, undecimated, dyadic, aliasing, and shift-invariant geometric multiscale ridgelet support vector transform (GMRSVT). Then, multiscale dictionaries are learned from examples to reduce noises existed in GMRSVT coefficients. MRSVF can extract the salient features associated with the linear singularities of images. Consequently, GMRSVT can well approximate edges, contours and textures in images, and avoid ringing effects suffered from sampling in the multiscale decomposition of images. It is new way for image representation and recovery, but it consumes much time than thresholding approaches. Santosh Kumar Yadav,Rohit Sinha and Prabin Kumar Bora introduced image denoising using ridgelet transform in a collaborative filtering framework[7] in 2007. They explored the use of ridgelet transform in collaborativeering framework and shown that the BM3D performs better with the ridgelet transform than with the wavelet transform for the denoising textured image. For non-textured images, the method was found to be slightly inferior to the BM3D algorithm in homogeneous regions only.

In 2015 March Han liu,Yue Zhao,Lili Liang and Yingmin Yi introduced image denoising using patch based Singular Value Decomposition(SVD)[8]. Image patches are grouped together from a noisy image.2D SVD was followed by 1D SVD. This 2 stage method showed better performance than other existing methods. Finally Qiang Guo, Caiming Zhang, Yunfeng Zhang, and Hui Liu introduced an efficient SVD-Based method for image denoising[9]. By using the nonlocal self-similarity and the low-rank approximation,the algorithm was computationally simple. Firstly, the method classifies similar image patches by the block matching technique to form the similar patch groups, which results in the similar patch groups to be low-rank. Next, each group of similar patches is factorized by singular value decomposition (SVD) and estimated by taking only a few largest singular values and corresponding singular vectors. Lastly, an initial denoised image is generated by aggregating all processed patches. For low-rank matrices, SVD can provide the optimal energy compaction in the least square sense. But it requires some more methods for solving images with large singular patches.

The next of the paper is organized as follows. Noise model is given in section 2. Section 3 outlines the proposed method. Simulation results and performance analysis is given in section 4. Finally, the section 5 deals with concluding remarks and future work.

II. NOISE MODEL

Different types of noise that can contaminate an image are gausssian,speckle,salt and pepper etc.

y=x+e;

y is the noisy image, x is the original clear image, e is the noise added.

x and e are uncorrelated. Noise lies in the low power region in frequency spectrum. Gaussian Noise is caused by random fluctuations in the signal. It is modeled by random values added to an image. Salt and pepper noise is also known as Impulse Noise. This noise can be caused by sharp & sudden disturbances in the image signal. Its appearance is randomly scattered white or black (or both) pixel over the image. Speckle noise can be modeled by random values multiplied by pixel values of an image. In the proposed paper we compare different techniques to denoise images affected by these noise. PSNR is calculated and compared for all the techniques.

III. PROPOSED METHOD

We propose an efficient method to estimate the noise-free image by combining patch grouping with the low-rank approximation of SVD (abbreviated as LRA-SVD), which leads to an improvement of denoising performance. Patch grouping step identifies similar image patches by the Euclidean distance based similarity metric. Ridgelet transform is applied to the obtained image.

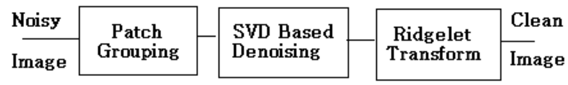

Fig.1 Block diagram of proposed method

A. Patch Grouping

Grouping similar patches, as a classification problem, is an important and fundamental issue in image and video processing with a wide range of applications. While there exist many classification algorithms available in the literature, e.g., block matching, K-means clustering, nearest neighbor clustering and others, we exploit the block matching method for image patch grouping due to its simplicity. Euclidean distance from the transform coefficients is used to identify the similar square patches.

B. Singular Value Decomposition

Image is divided into patches. A similar group of patches is takenbased on Euclidean distance and SVD ia applied.

$\mathbf{P} = \mathbf{U\Sigma V^T} = \Sigma\sigma_i \boldsymbol{u_i} \boldsymbol{v_i}^{T}$

U [and] V are unitary matrices. $\mathbf{\Sigma}$ =diag(σ1, . . . , σn) has nonnegative diagonal elements appearing in nonincreasing order such that

$\sigma_1 \geq \sigma_2 \geq . . . \geq \sigma_n \geq 0.$

The diagonal entries σ_i of $\mathbf{\Sigma}$ are called the singular values of P while the vectors u_i and vi are the left and right singular vectors of P, respectively.

By low rank approximation,

$\mathbf{P}_k = \mathbf{U\Sigma}_k\mathbf{V}^T$

where $\mathbf{\Sigma}_k$ is obtained from the matrix $\mathbf{\Sigma}$ by setting thediagonal elements to zeros but the first *k* singular values, i.e.

$\mathbf{\Sigma}_k = \text{diag}(\sigma_1, . . . , \sigma_k, 0, . . . , 0).$

After applying the low-rank approximation we aggregate estimates of the patches to obtain its denoised version. SVD is computationally fast. It fills the missing pixels in an image. Its non-local redundancy and low rank approximation attenuate noise. But it requires some more methods for solving images with large singular patches. For that ridgelet transform is applied.

C. Ridgelet Transform

Ridgelet transform is able to compete with the wavelet transform in image restoration. It deals better with line discontinuities. The ridgelet transform can compress the energy of the image into a smaller number of ridgelet coefficients.

1. Compute the 2D FFT of the image.
2. Substitute the sampled values of the Fourier transform obtained on the square lattice with sampled values on a polar lattice.
3. Compute the 1D inverse FFT on each angular line.

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4. Perform the 1D dual-tree complex wavelet transform on the resulting angular lines in order to obtain the ridgelet coefficients.

The complex ridgelet image denoising algorithm can be described as follows:

1. Partition the image into R × R blocks with two vertically adjacent blocks overlapping R/2 × R pixels and two horizontally adjacent blocks overlapping R × R/2 pixels

2. For each block, Apply the proposed complex ridgelets, threshold the complex ridgelet coef- ficients, and perform inverse complex ridgelet transform.

3. Take the average of the denoising image pixel values at the same location.

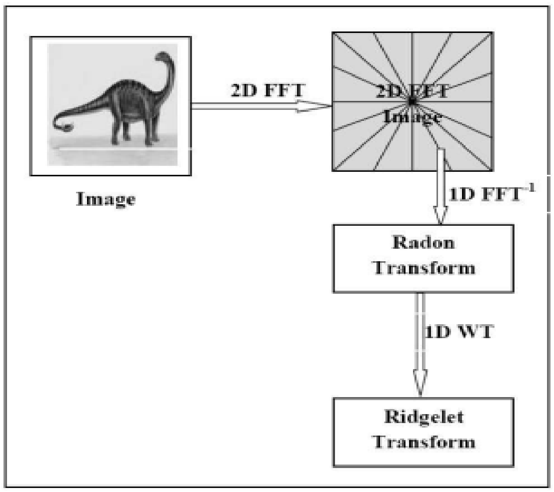

Fig.2 Flowchart of Discrete ridgelet transform.

IV. Simulation Results And Performance Analysis

Image denoising using DCT, DWT, SVD and the proposed method have been tested on images affected by different types of noise. performance results are given in figures below.

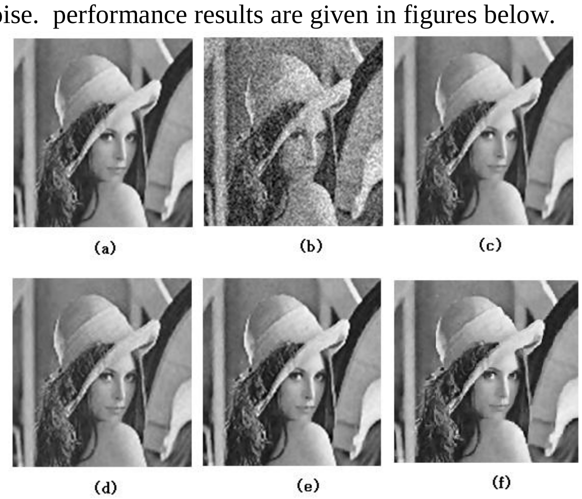

Fig 3. Denoising image affected by AWGN. (a)clean image(b)noisy image (c) denoised using DCT (d) denoised using DWT (e) denoised using SVD (f)proposed method

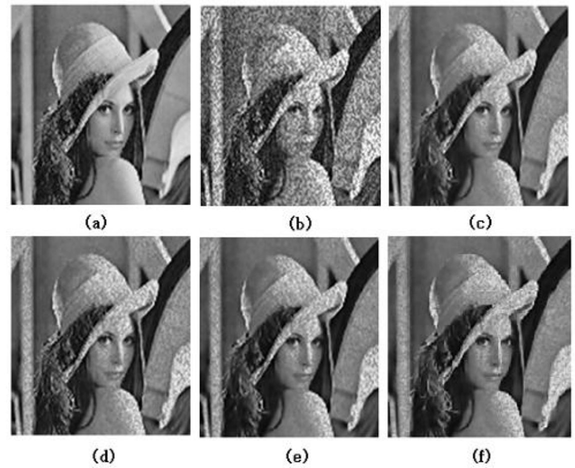

Fig 4. Denoising image affected by speckle.(a)clean image(b)noisy image (c)denoised using DCT (d) denoised using DWT(e) denoised using SVD (f)proposed method

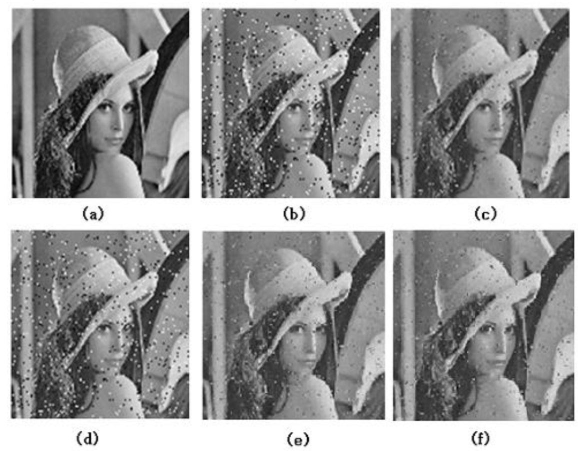

Fig 5. Denoising image affected by salt and pepper noise.(a)clean image (b)noisy image (c)denoised using DCT (d) denoised using DWT (e) denoised using SVD (f)proposed method

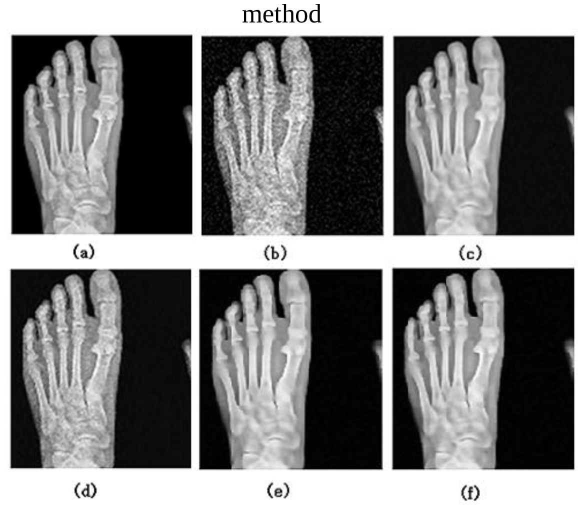

Fig 6. Denoising xray image affected by AWGN.(a)clean image(b)noisy image (c)denoised using DCT (d) denoised using DWT(e) denoised using SVD (f)proposed method

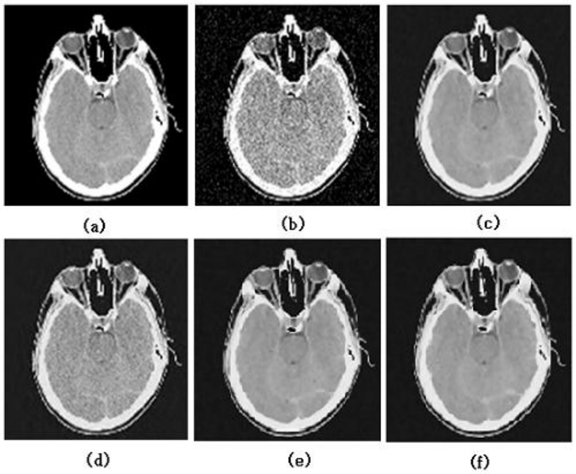

Fig.7. Denoising chest scan image affected by AWGN.(a)clean image(b)noisy image (c)denoised using DCT (d) denoised using DWT(e) denoised using SVD (f)proposed method

Table1. Comparison Of The PSNR (Db) AN Of Different Denoising Methods On Test Image With Different Types Of Noise .

NOISE	DCT	DWT	SVD	PROPOSED
AWGN	30.8059	30.097	31.5946	32.1259
SPECKLE	27.29	26.5681	27.4839	27.9902
SALT AND PEPPER	24.9335	18.9857	24.443	25.0239

Table2. Comparison Of The PSNR (Db) Of Different Denoising Methods On Different Images Affected With AWGN

IMAGE	DCT	DWT	SVD	PROPOSED
LENA	30.8059	30.097	31.5946	32.1259
FOOT	28.6582	28.3442	29.3633	29.8582
CHEST	27.101	25.8056	27.9517	28.4531

Table 1 shows the comparison of the PSNR (dB) an of different denoising methods on test image with different types of noise . Table 2 shows comparison of the PSNR(dB) of different denoising methods on different images affected with awgn.

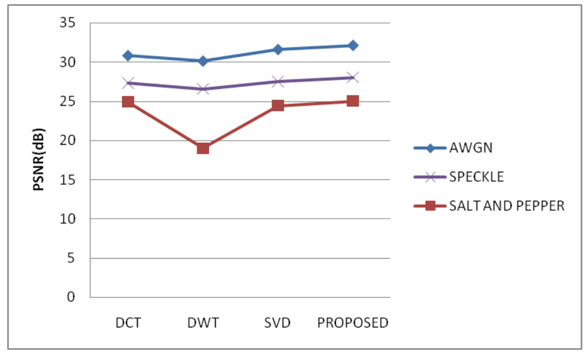

Fig. 8.Comparision of the PSNR (dB) of different denoising methods on test image affected with different types of noise

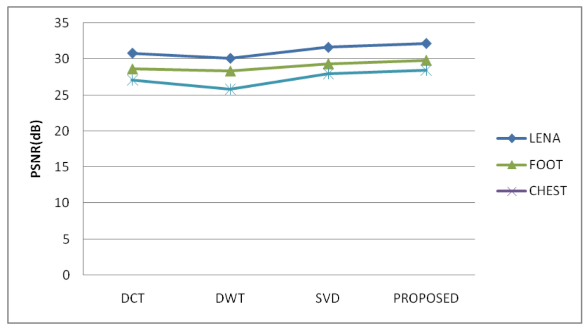

Fig. 9.Comparison of the PSNR(dB) of different denoising methods on different images affected with AWGN.

V.Conclusion And Future Work

In this paper several denosing techniques are compared. Experimental results demonstrate that the proposed method gives better PSNR compared to all other methods. Also, results shows that roposed method works well for images affected with additive white Gaussian noise. This method can be used for denoising medical images which is the most important application of denoising. Our method can be extended to color images and video denoising.

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