Comparing study using DWT / CT transforms in image denoising process

Iman Qays Abduljaleel *Amal Hameed Khaleel* *Suhad Muhajer Kareem*
emankais@yahoo.com *amal_albahrany@yahoo.com* *suhad_althaher83@yahoo.com*

Basra University\ Science Collage\ Computer Science Dept.

Abstract

Images may contain different types of noises; removing noise from image is often the first step in image processing, and remains a challenging problem in spite of the sophistication of recent research.

This paper presents an efficient image denoising scheme based on two types of multi-resolution transforms, namely, the Discrete Wavelet Transform (DWT) and the Curvelet Transform(CT). each subbands components of an uses transform are denoising using two steps: 1) passed through principal component analysis (PCA) denoising procedure. 2) The image data obtain from PCA procedure can be denoising either by hard or soft thresholding techniques. The effectiveness of the methods was compared using parameters like MSE and PSNR. We find that using CT more efficient then using DWT and the qulity of denoising increase when we using PCA denoising procedure.

Use the matlab version of 8th in the different treatment stages.

Keywords: image denoising , wavelet transform, curvelet transform, PCA, soft thresholding, hard thresholding.

I. Introduction

Image denoising is a procedure in digital image processing aiming at the removal of noise, which may corrupt an image during its acquisition or transmission, while retaining its quality [S.Satheesh et.al 2011]. Although many related studies have been done, developing a method that is capable to suppress the additive noise totally from the noisy image without corrupting the image details is still a challenging task. Hence, the required essential criteria in designing a denoising technique are: 1) the additive noise in smooth regions should be completely removed, 2) the edges should not be blurred or sharpened, 3) the texture details should be maintained, 4) the overall contrast should be preserved and 5) the additional artifacts should not be appeared in the restored image. However, it is very difficult to develop a denoising method that matches all the mentioned criteria [S. Suhaila et.al 2010].

over the last decade, there has been abundant interest in wavelet methods for noise removal in signals and images. The new ridgelet and curvelet transforms were developed over several years in an attempt to break an inherent limit plaguing wavelet denoising of images. This limit arises from the well-known and frequently depicted fact that the two-dimensional (2-D) wavelet transform of images exhibits large. Wavelet coefficients even at fine scales, all along the important edges in the image, so that in a map of the large wavelet coefficients one sees the edges of the images repeated at scale after scale. While this effect is visually interesting, it means that many wavelet coefficients are required in order to reconstruct the edges in an image properly [J. Starck et.al 2002]. In non-linear techniques, wavelet based image denoising methods have attracted due to multi-resolution nature and ability to produce high level of noise reduction. Wavelet fails to give sparse representation along c^2 curve. Wavelet effectively represents discontinuities for one dimensional signal. Curvelet transform (CT) overcomes limitations of wavelet transform (WT). CT is a multiscale pyramid with many direction and position at each length scale and needle shaped element at fine scale [Anil et.al 2010].

The organization of the paper is as follows: section 2 contented the basic principles used in this paper, section 3 satisfied the proposed algorithm, section 4 presents experiment results and section 5 concludes the paper.

II. Basic Principles

1. Discrete Wavelet Transform(DWT)

The DWT is identical to a hierarchical subband system where the subbands are logarithmically spaced in frequency and represent octave-band decomposition. Due to the decomposition of an image using the DWT the original image is transformed into four pieces which is normally labeled as LL, LH, HL and HH as in the schematic depicted in Fig. 1 a. The LL subband can be further decomposed into four subbands labeled as LL2, LH2, HL2 and HH2 [H. Dhillon et.al 2011].

As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides a non redundant and unique representation of the signal. Several properties of the wavelet transform, which make this representation attractive for denoising, are [H. Dhillon et.al 2011] :

- Multiresolution - image details of different sizes are analyzed at the appropriate resolution scales.
- Sparsity - the majority of the wavelet coefficients are small in magnitude.
- Edge detection - large wavelet coefficients coincide with image edges.
- Edge clustering - the edge coefficients within each sub band tend to form spatially connected clusters

2. Curvelet Transform(CT)

CT is one of the latest developments of non-adaptive transforms today. Compared to wavelet, curvelet provides a more sparse representation of the image, with improved directional elements and better ability to represent edges and other singularities along curves[B. Zhang et.al 2011]. Curvelets have useful geometric features that set them apart from wavelets. It uses the ridgelet transform as a component step and implements curvelet subbands using a filter bank of wavelet filters. This transform combines multiscale ridgelets with a spatial bandpass filtering operation to isolate different scales. While ridgelets have global length and variable widths, curvelets in addition to a variable width have a variable length and so a variable anisotropy [J. Starck et.al 2002].

The decomposition is the sequence of following steps (see Fig. 1) [J. Starck et.al 2002]:

1.Subband decomposition: The image f is decomposed into subbands such that :

$$f \rightarrow (P0\ f, \Delta 1\ f, \Delta 2\ f, ...) .$$

2.Smooth partitioning: Each subband is then smoothly windowed into squares.

3.Renormalization: Each resulting square is renormalized to unit scale

4.Ridgelet analysis: Each square is analyzed via the discrete ridgelet transform.

Both curvelets and ridgelets take the form of basis elements which exhibit very high directional sensitivity and are highly anisotropic. Both occur at all scales, locations, and orientations. However, whereas ridgelets have unit length, curvelets occur at all dyadic lengths and exhibit an anisotropy increasing with decreasing scale like a power law. Curvelet obeys a scaling relation where by the width of a curvelet element is about the square of its length; i.e. width ~ length^2 [A. Majumdar et.al 2007].

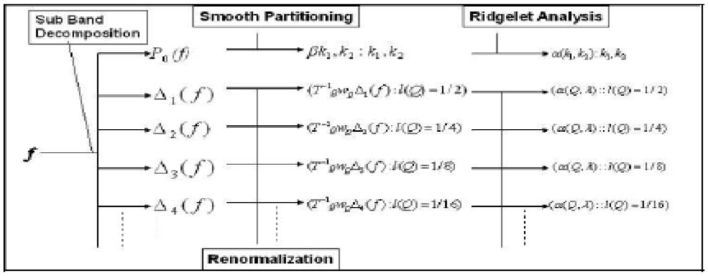


Fig.1 : Overview of Curvelet Transform Scheme.

3. Principal Component Analysis (PCA)

PCA is one of the most well known methods for data analysis. The objective of this method is dual. Primarily it is to massage input data in a form where the multiple dimensions of the input data are mutually decorrelated. As a side effect the significance of each decorrelated dimension, in terms of energy contribution in the original input, is also estimated. Upon concluding the computations the user is presented with a ranking on which dimensions are most important and based on this ranking we can throw away non-important dimensions and reduce the dimensionality of the data with minimal side effects[Pierre 2005].

Let us consider a set of N sample images {X1,X2,…,XN} of d*d dimensions be an ensemble of vectors and Let be the average vector in the ensemble.

$$E(X)=\frac{1}{N}\sum_{n=1}^{N}X_n \qquad \text{...(1)}$$

After subtracting the average from each element of X, we get a modified ensemble of vectors X'= {X'1,X'2,…,X'N} with

$$\bar{X}_n = X_n - E(X). \qquad \text{...(2)}$$

The auto-covariance matrix M for the ensemble X is defined by

$$M=\mathrm{cov}(\bar{X})=E(\bar{X}\otimes\bar{X}) \qquad \text{...(3)}$$

Where M is $d^2 * d^2$ matrix, with elements

$$M(i,j)=\frac{1}{N}\sum\bar{X}_n(i)\bar{X}_n(j), 1\le i.j\le d^2 \qquad \text{...(4)}$$

We extract the eigenvectors of M as columns in a matrix **V** and its eigenvalues as diagonal entries in a matrix A [Pierre 2005, Masoud et.al 2008].

4. Salt and pepper noise

Salt and pepper noise is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels. A “spike” or impulse noise drives the intensity values of random pixels to either their maximum or minimum values. The resulting black and white flecks in the image resemble salt and pepper[G. Iango et.al 2011].

5. Thresholding Techniques

Thresholding is a procedure which takes place after decomposing a signal at a certain decomposition level. A threshold is applied to coefficients for each level from 1 to N (last decomposition level). By applying a hard threshold the coefficients below this threshold level are zeroed, and the output after a hard threshold is defined by this equation[J. Karam 2008] :-

$$y_{hard}(t) = \begin{cases} x(t), & |x(t)| > \delta \\ 0, & |x(t)| \le \delta \end{cases} \qquad \text{...(5)}$$

where x(t) is the input speech signal and δ is the threshold. An alternative is soft thresholding at level δ which defined by this equation [Pierre 2005] :-

$$y_{soft}(t) = \begin{cases} sign(x(t))(|x(t)| - \delta), & |x(t)| > \delta \\ 0, & |x(t)| \le \delta \end{cases} \qquad \text{...(6)}$$

III. Proposed algorithm

This section describes the image denoising algorithm. The algorithm is very simple to implement and computationally more efficient (see Fig. 2).

We can see in Fig. 2 that we converted an input image to noised image by using salt and pepper noise because this type of noise is caused by errors in data transmission and we can measured the performance of proposed algorithm by using this type of noise.

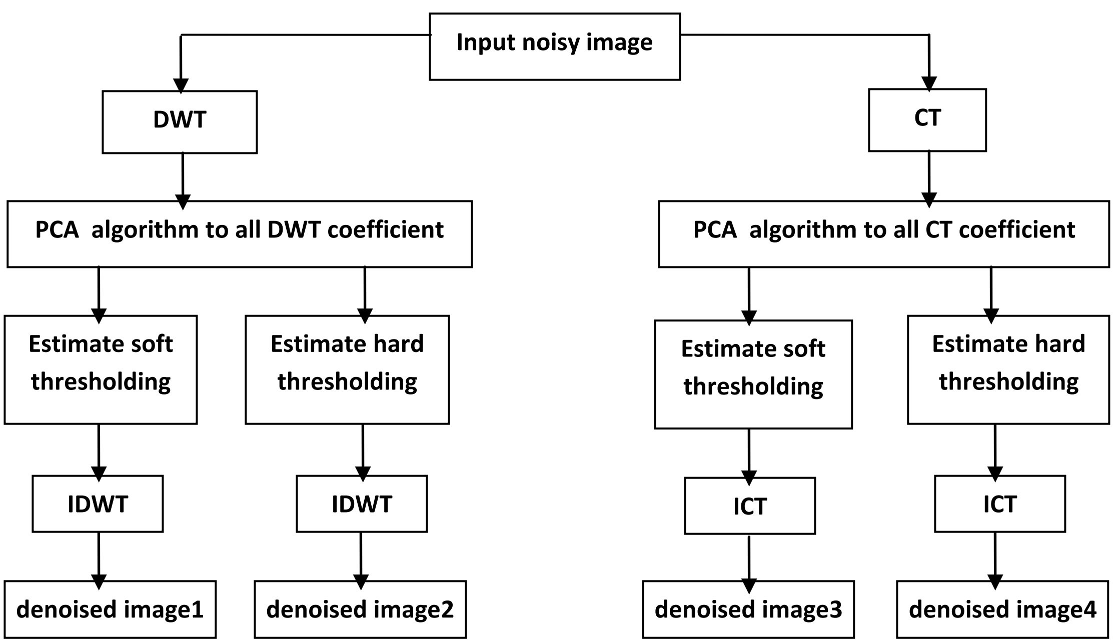


Fig. 2: proposed algorithms scheme.

The wavelet denoising method consists of the following steps:

- Calculate the DWT of the input image at scale 2 and mother wavelet db1.

- For each subband coefficients *c*alculate the PCA algorithm using Kaiser's rule to zeros all value less than Kaiser’s value.
- Using thresholding (hard or soft) to denoising each DWT subband coefficients.
- Reconstruct the denoised image from the modified DWT coefficients by using inverse DWT (IDWT).

Another algorithm was proposed by using another multi-resolution transform which named Curvelet transform (CT) and we can defined as below:

- Calculate the CT of the input image at scale 2 and angle 8. We get a set of subbands wj, each subband wj contains Nj coefficients and corresponds to a given resolution level.
- For each subband coefficients *c*alculate the PCA algorithm using Kaiser's rule to zeros all value less than Kaiser’s value.
- Using thresholding : If a CT subband coefficients is smaller than a predefined threshold it will be set to zero; otherwise it will shrunk in the absolute value by an amount of the threshold, this function named soft thresholding. Same as soft threshold If a CT subband coefficients is smaller than a predefined threshold it will be set to zero; otherwise it kept unchanged, this function named hard thresholding. So we can see that thresholding step performed the first action of image denoising by removing unaccepted value less than threshold value.
- Reconstruct the denoised image from the modified CT coefficients by using inverse CT (ICT).

We use statistical tool to measure the enhancement of images. The Root Mean Square Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR) are used to evaluate the enhancement of images [L.R. Litwin 1998].

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[R(x,y)-T(x,y)]^2}{(M \times N)}} \quad \text{...(7)}$$

$$PSNR = 10 \cdot \log_{10}\left(\frac{(L-1)^2}{\mathrm{RMSE}}\right) \quad \text{...(8)}$$

IV. Experiment Result

The results of the proposed method are tested on different Gray-Scale images such as cameraman.jpg and lena.jpg of size (512*512 pixels). The collected testing images are corrupted by salt and pepper noise and then these are used for proposed denoising algorithm. Fig. 4 and Fig. 5 illustrates the denoising algorithms results (PSNR and RMSE) .

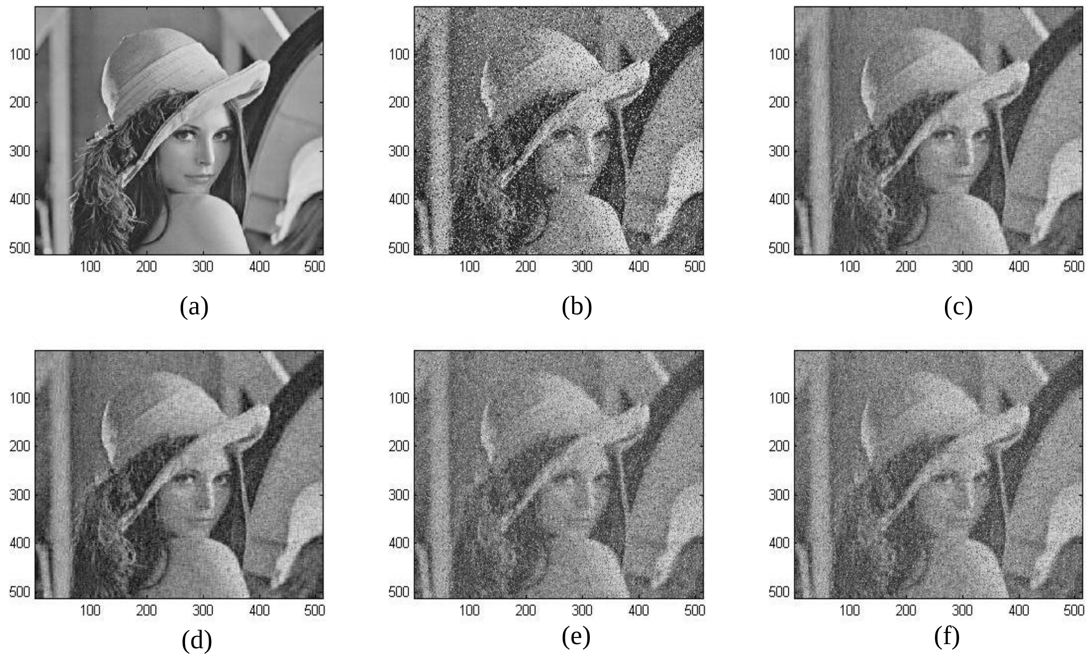
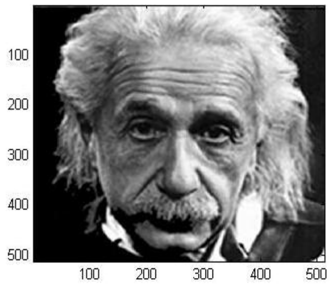
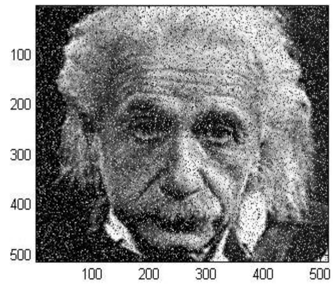


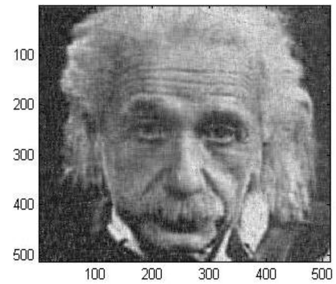
Fig.4 : (a) original image1, (b) image1 with salt and pepper noise, (c) denoised image1 by CT_PCA_HARD algorithm (PSNR=16.8429 , RMSE=181.28), (d) denoised image1 by CT_PCA_SOFT algorithm (PSNR=15.6577 , RMSE= 211.51), (e) denoised image1 by DWT_PCA_HARD algorithm (PSNR=20.3849, RMSE=121.01), (f) denoised image1 by DWT_PCA_SOFT algorithm(PSNR= 20.3246, RMSE=127.39)



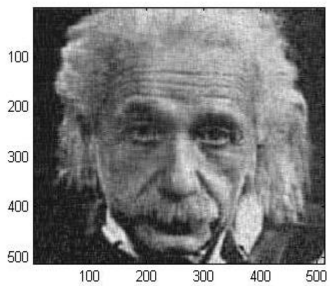
(a)



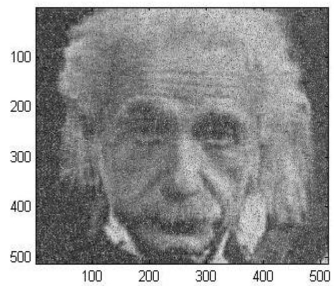
(b)



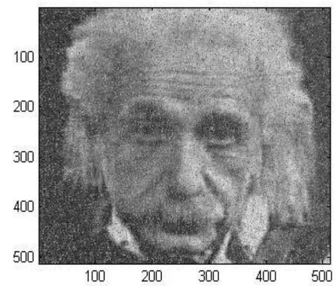
(c)



(d)



(e)



(f)

Fig.5 : (a) original image2, (b) image2 with salt and pepper noise, (c) denoised image2 by CT_PCA_HARD algorithm (PSNR=16.1436 , RMSE=1580.2), (d) denoised image2 by CT_PCA_SOFT algorithm (PSNR=14.9043, RMSE= 2103.01), (e) denoised image2 by DWT_PCA_HARD algorithm (PSNR=19.2042, RMSE=781.02) , (f) denoised image2 by DWT_PCA_SOFT algorithm (PSNR= 19.179, RMSE=785.55)

V. Conclusion

In this work, we have introduced various techniques for removal of Salt and pepper noise from images. To find the most important value in each CT/DWT coefficients we used PCA algorithm to removed non-important CT/DWT coefficients. At different scales the CT/DWT coefficients vary, therefore we applied the thresholding functions (soft and hard thresholding). The performance of proposed algorithms is measured using quantitative performance measures such as RMSE and PSNR. The experimental results indicate that the CT is more efficient than DWT and it gives the best results after using PCA algorithm in CT coefficient . The proposed method is simple and easy to implement.

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دراسة مقارنة لتحويلي (DWT/CT) المستخدمان في معالجة تنقية الصور

ايمان قيس عبد الجليل **امل حميد خليل** **سهاد مهجر كريم**

emankais@yahoo.com **amal_albahrany@yahoo.com** **suhad_althaher83@yahoo.com**

جامعة البصرة\ كلية العلوم \ قسم علوم الحاسبات

المستخلص

تحتوي الصور أنواعا مختلفة من الضوضاء، ولهذا تعتبر محاولة إزالة هذه الضوضاء الخطوة الأولى ضمن سلسلة خطوات معالجة تلك الصورة والتي لازالت تعد تحديا للكثير من الباحثين العاملين في هذا المجال.

ومن خلال هذا البحث نقدم آلية مقترحة لإزالة احد انواع الضوضاء بالاعتماد على نوعين من التحويلات المتعددة الدقة multi-resolution، وهي التحويل المويجي المتقطع Discrete Wavelet Transform(DWT) وتحويل Curvelet (CT) . وبحسب التحويل المستخدم نقوم بتنقية العناصر المكونة لكل حزمة جزئية subband من الحزم المكونة للصورة الأصلية باستخدام الخطوتين التاليتين : 1) تمرير الكتلة المحددة من العناصر إلى خوارزمية principal component analysis (PCA) .2) البيانات المنقاة التي نحصل عليها من خوارزمية PCA تنقى مرة أخرى باستخدام خوارزمية hard thresholding او خوارزمية soft thresholding.

تقاس كفاءة الأنظمة المقترحة بالاعتماد على المقياسين MSE و PSNR. وقد وجدنا ان استخدام تحويل Curvelet كان أكثر كفاءة مقارنة بالتحويل المويجي المتقطع DWT ، وازدادت كفاءته عند إلحاقه بخوارزمية PCA. وقد تم استخدام برنامج matlab (R2011a) في كل مراحل المعالجة.