International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161

Available at http://inpressco.com/category/ijcet

Research Article

Image Denoising using Curvelet Transform

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Accepted 20 Feb 2015, Available online 26 Feb 2015, **Vol.5, No.1 (Feb 2015)**

Abstract

In this paper we propose a new method to reduce noise in digital image. Images corrupted by Gaussian Noise are still a classical problem. To reduce the noise or to improve the quality of image we have used two parameters i.e. quantitative and qualitative. For quantity we will compare peak signal to noise ratio (PSNR). Higher the PSNR better the quality of the image. The Curvelet transform is a higher dimensional generalization of the Wavelet transform designed to represent images at different scales and different angles .In this paper we proposed a Curvelet Transformation based image denoising, which is combined with weiner filter in place of the low pass filtering in the transform domain. We demonstrated through simulations with images contaminated by three different noise i.e. Gaussian, salt and Pepper and speckle. Experimental results show that our proposed method gives comparatively higher peak signal to noise ratio (PSNR) value, are much more efficient and also have less visual artifacts compared to other existing methods.

Keywords: *Curvelet transform, Discrete wavelet transform, Discrete curvelet Transform, Filter, PSNR.*

1. Introduction

Image processing is any form of signal processing for which the input is an image, such as photographs or frames of video and the output of image processing can be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

De-noising of natural images corrupted by noise using curvelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. The curvelet de-noising scheme thresholds the curvelet coefficients arising from the curvelet transform. The curvelet transform yields a large number of small coefficients and a small number of large coefficients.

Simple de-noising algorithms that use the curvelet transform consist of three steps.

• Calculate the curvelet transform of the noisy signal.

• Modify the noisy curvelet coefficients according to some rule.

• Compute the inverse transform using the modified coefficients.

Discrete curvelet transform is one of the most powerful approaches in capturing edge curves in an image. Related works on curvelet features are also investigated. In this research, we generate a texture features descriptor using wrapping based discrete curvelet transform. This descriptor is used to represent images in a large database in terms of their features and to measure the similarity between images. The retrieval outcome shows, the proposed curvelet texture feature descriptor outperforms the Gabor filters in both retrieval accuracy and efficiency. The optimal level of curvelet decomposition is also investigated to obtain the highest retrieval outcome in terms of effectiveness and efficiency. From the experimental results, we find that curvelet texture feature is robust to a reasonable scale distortion

2. Curvelet Transform

Curvelet transform can sparsely characterize the high-dimensional signals which have lines, curves or hyper plane singularities. (V Vijay Kumar et al ,2014).Curvelet transform has been developed to overcome the limitations of wavelet though wavelet transform has been explored widely in various branches of image processing, it fails to represent objects containing randomly oriented edges and curves as it is not good at representing line singularities. Gabor filters are found to perform better than wavelet transform in representing textures and retrieving images due to its multiple orientation approach. However, due to the loss of spectral information in filters they cannot effectively represent images. This affects the CBIR performance. Consequently, a more robust mechanism is necessary to improve CBIR performance. To achieve

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a complete coverage of the spectral domain and to capture more orientation information, curvelet transform has been developed.

The initial approach of curvelet transform implements the concept of discrete ridgelet transform J.-L. Starck. Since its creation in 1999 (E.J. Candès *et al,* 1999). , ridgelet based curvelet transform has been successfully used as an effective tool in image denoising, (J.-L. Starck *et al,* 2002). image decomposition, texture classification (D. Zhang, *et al,* 2000). Image deconvolution (E.J. Candès *et al,* 1999), astronomical imaging and contrast enhancement (M. J. Fadili *et al,* 2007), etc. But ridgelet based curvelet transform is not efficient as it uses complex ridgelet transform (M.J. Fadili *et al,* 2007),In 2005, Candès et al. proposed two new forms of curvelet transform based on different operations of Fourier samples (E.J. Candès *et al,* 2005), namely, unequally-spaced fast Fourier transform (USFFT) and wrapping based fast curvelet transform. Wrapping based curvelet transform is faster in computation time and more robust than ridgelet and USFFT based curvelet transform (M. J. Fadili *et al,* 2007).To our knowledge, wrapping based curvelet transform has not been used in CBIR and there is no work on a systematic evaluation of curvelet in CBIR.

3. Discrete Curvelet Transform

Basically, curvelet transform extends the ridgelet transform to multiple scale analysis.

Therefore, we start from the definition of ridgelet transform. Given an image the continuous ridgelet coefficients are expressed as (J.-L. Starck *et al,* 2002).

$$f(a, b, \theta) = \iint \psi_{a, b, \theta}(x, y) f(x,y)dxdy$$

Here, a is the scale parameter where $a > 0$, $b \in R$ is the translation parameter

And $\theta \in [0, 2\pi)$

A ridgelet can be defined as (J.-L. Starck *et al,* 2002).

$$\Psi a, b, \theta(x, y) = a^{-\frac{1}{2}}\Psi(\frac{x\cos\theta + y\sin\theta - b}{a})$$

where θ is the orientation of the ridgelet. Ridgelets are constant along the lines.

The contrast between wavelet and ridgelet on capturing edge information is shown in Fig.1. It can be observed that the curvelets, at all scales, capture the edge information more accurately and tightly than wavelets.

The ridgelet based curvelet transform is a combination of the wavelet transform and the Radon transform.

In this curvelet approach, input image is first decomposed into a set of subbands each of which is then partitioned into several blocks for ridgelet analysis. The ridgelet transform is implemented using the Radon transform and the 1-D wavelet transforms (J.-L. Starck *et al,* 2002). During the ridgelet transform, one of the processes is the spatial partitioning which involves overlapping of windows to avoid blocking effects. It results in a large amount of redundancy. Moreover, this process is very time consuming, which makes it less feasible for texture features analysis in a large database (M. J. Fadili *et al,* 2007).

Fast discrete curvelet transform based on the wrapping of Fourier samples has less computational complexity as it uses fast Fourier transform instead of complex ridgelet transform.

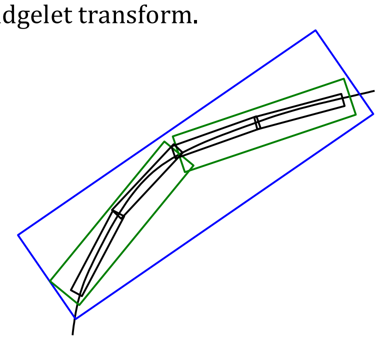

Fig. 1 From wavelet transform

In this approach, a tight frame has been introduced as the curvelet support to reduce the data redundancy in the frequency domain (M.J. Fadili *et al,* 2007).Normally, rideglets have a fixed length that is equal to the image size and a variable width, whereas curvelets have both variable width and length and represent more anisotropy. Therefore, the wrapping based curvelet transform is simpler, less redundant and faster in computation (M.J. Fadili *et al,* 2007).than ridgelet based curvelet transform. We now discuss discrete curvelet trφnsform based on wrapping Fourier (E.J. Candès *et al,* 2005).As it is the most promising approach of curvelet so far, we intend to use it for texture representation in our CBIR research.

4. Discrete Wavelet Transform

Wavelet transform is introduced with the advancement in multiresolution transform research. Discrete wavelet transform is one of the most promising multiresolution approaches used in CBIR. It has the advantage of a time-frequency representation of signals where Fourier transform is only frequency localized. The location, at which a frequency component of an image exists, is important as it draws the discrimination line.

Unlike the FT and STFT, the window size varies at each resolution level when the wavelet transform is applied to an image. In discrete wavelet transform, the original image is high-pass filtered yielding three detail images, describing the local changes in horizontal, vertical and diagonal direction of the original image. The image is then low- pass filtered yielding an approximation image which is again filtered in the same manner to generate high and low frequency subbands at the next lower resolution level This process is continued until the whole image is processed or a level is determined as the lowest to stop decomposition. This continuing decomposition process is known as down sampling and shown in Fig 2.

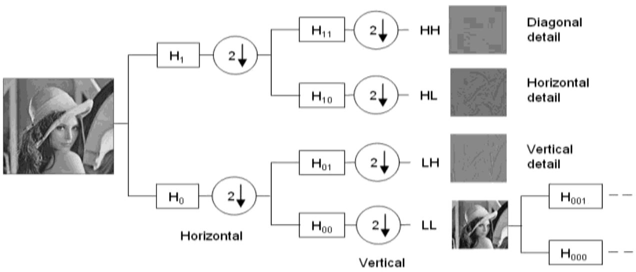

Fig. 2 Decomposition process

The whole decomposition process provides us with an array of DWT coefficients obtained from each subbands at each scale. These coefficients can then be used to analyze the texture patterns of an image. Wavelet subbands obtained from the Lena image using 4 decomposition levels are shown in Fig 3.

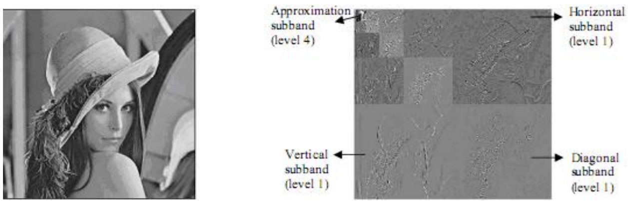

Fig. 3 Wavelet subbands obtained from the Lena image using 4 decomposition levels

4. Main objective

1. To study all the methods of the Denoising.
2. Attenuate the color frequencies using Gabor Filter and Weiner Filter
3. Applying the Curvelet Transform.
4. Compare the image quality using PSNR Tool

Proposed algorithm steps:

- ***Step I:*** Take noisy image.

- ***Step II:*** Applying Curvelet Transform as under:

(a) Sub Band Decomposition
(b) Smooth Portioning
(c) Renormalization
(d) Ridgelet Analysis

- ***Step III:*** In Sub Band Decomposition

(a) Divide image into resolution layers
(b) Each layer contains details of different frequencies.
(c) These frequencies are attenuates and approximate with the help of Gabor Filter.

- ***Step VI***: For Reconstruction inverse of curvelet transform is performed.
- ***Step V*** : Output is the final Denoised image.

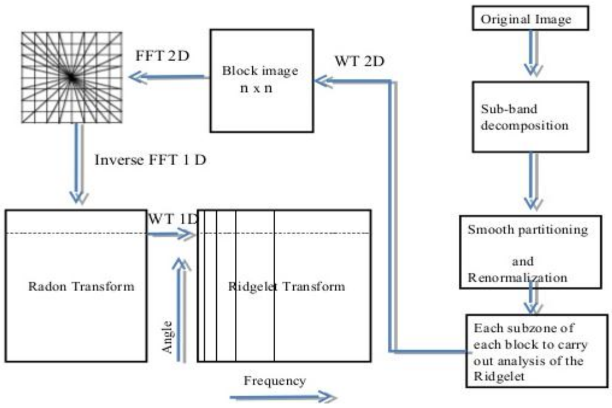

Fig. 4 Process of Curvelet Transform

5. Result


Fig.5 Noisy Figure

Fig.6 Output Figure
PSNR =89.8995


Fig. 7 Noisy figure

Fig.8 Output Figure
PSNR = 97.4697


Fig. 9 Noisy figure

Fig.10 Output Figure
PSNR =93.5475

Table 1

S. No	Parameters	Values
	Noise	PSNR
1	Gaussian	89.8995
2	Salt and Pepper	97.4697
3	Speckle	93.5475

Conclusions

This paper presents a comparative analysis of various image denoising techniques using curvelet transforms. A lot of combinations have been applied in order to find the best method that can be followed for denoising intensity images. The image formats that have been used in this work are JPG, BMP, TIF and PNG.

The analysis, of all the obtained experimental results, demonstrates that curvelet transform outperforms other transform for denoising all of the above mentioned images.

• Curvelet transform denoises the images with more precision as compared to DWT because of its inborn quality of keeping the data intact to a greater extent.

• In this various filters have been used all together in order to achieve the best results.

• PSNR shows an apprehensive improvement, if the noisy images are denoised using curvelet transform

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