DENOISING OF COMPUTED TOMOGRAPHY IMAGES USING IMPROVED CURVELET TRANSFORMATION

Tanjeet Kaur*

Gaurav Gupta**

Gagandeep Kaur***

ABSTRACT

The purpose of this paper is to carry out the performance assessment of the noise reduction methods on the brain Computed Tomography (CT) images.This Work proposes a Curvelet Transformation based image denoising, which is combined with Gabor filter in place of the low pass filtering in the transform domain. This study is focused not only on the noise suppression but also on fine details and edge preservation.

Keywords: *Computed Tomography, Curvelet transform, Gabor filter.*

*M.Tech Student, Punjabi University, CSE Department, University College of Engineering, Patiala, Punjab, India

**Associate Professor, Punjabi University, CSE Department, University College of Engineering, Patiala, Punjab, India

***Assistant Professor, Punjab Technical University (PTU), CSE Department, RIMT-IET, Mandi-Gobindgarh, Punjab, India

I. INTRODUCTION

Computed Tomography (CT) and magnetic resonance imaging (MRI) are the two modalities that are regularly used for brain imaging. CT imaging is preferred over MRI due to lower cost, short imaging times, widespread availability, ease of access , optimal detection of calcification and hemorrhage and excellent resolution of bony detail. CT scans of internal organs, bone and soft tissue provide greater clearness than conventional x-ray. However, the limitations for CT scanning of head images are due to partial volume effects which affected the edges and produce low brain tissue contrast [1]. CT is a radiographic inspection method that generates a 3-D image of the inside of an object from a large series of 2-D images taken on a cross sectional plane of the same object. CT generates thin slices of the body with a narrow X-ray beam, which rotates around the body of the stationary patient [2].

CT images are generally of low contrast and they often have a Gaussian noise due to various acquisitions, transmission storage and display devices [3],[4]. In most of the image processing applications, a suitable noise removal phase is often required before any relevant information could be extracted from analyzed images. In this area initial effort was started with ideas based on statistical filtering in spatial domain [5].

Over the last decade there has been wide attention for noise removal in signals and images based on wavelet methods. The wavelet coefficients at different scales could be obtained by taking Discrete Wavelet Transform (DWT) of the image. The small coefficients in the subbands are dominated by noise, while coefficients with large absolute value carry more signal information than noise. Replacing noisy coefficients by zero and an inverse wavelet transform may lead to reconstruction that has lesser noise. Normally Hard thresholding (Hard_WT) and Soft thresholding techniques are used for such denoising process. Although the hard and soft thresholding methods are widely used for noise removal purpose but they have some disadvantages. In case of hard thresholding, the wavelet coefficients are not continuous at the preset threshold so that it may lead to the oscillation of the reconstructed signal. The wavelet coefficients in case of soft thresholding method have good continuity, but it may cause constant deviations between the estimated wavelet coefficients and original wavelet coefficients. Thus the accuracy of the reconstructed image might suffer. There has been a lot of research on wavelet thresholding and threshold selection for signal and image denoising [6],[7],[8],[9]. To overcome above mentioned disadvantages, considerable improvements in perceptual quality were obtained by translation invariant methods based on thresholding of an undecimated wavelet transform [10],[11],[12].However as an optimal tool for 1-D signals, wavelet in 2-D images is only better at isolating the discontinuities at edge points but cannot detect the smoothness along the edges. Wavelet can only capture limited directional information. Due to these disadvantages of wavelet, theory of multiscale geometric analysis has been developed. In 1999 Donoho and others [13] proposed the concept of curvelet transform. Unlike wavelets, curvelets are localized not only in position and scale but also in orientation. This localization provides the curvelet frame with surprising properties; it is an optimally sparse representation for singularities supported on curves in two dimensions and has become a promising tool for various image processing applications[13],[14],[15],[16].

In this paper improved curvelet transformation is used to denoise computed tomography images This Work proposes a Curvelet Transformation based image denoising, which is combined with Gabor filter in place of the low pass filtering in the transform domain. This analysis is not only focused on the suppression of noise but also on preservation of fine details and edges. The quality assessment metrics used are Signal-to-noise-ratio (SNR), Peak-signal-to-noise-ratio

II. CURVELET TRANFORMATION

The Curvelet transform is a higher dimensional generalization of the Wavelet transform designed to represent images at different scales and different angles. Curvelets enjoy two unique mathematical properties, namely:

Curved singularities can be well approximated with very few coefficients and in a non-adaptive manner - hence the name "curvelets". Curvelets remain coherent waveforms under the action of the wave equation in a smooth medium.

Curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific computing.Curvelets are an appropriate basis for representing images (or other functions) which are smooth apart from singularities along smooth curves, where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale. This property holds for cartoons, geometrical diagrams, and text. As one zooms in on such images, the edges they contain appear increasingly straight. Curvelets take advantage of this property, by defining the higher resolution curvelets to be skinnier the lower resolution curvelets. However, natural images (photographs) do not have this property; they have detail at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale.

Curvelet Transform give a superior performance in image denoising due to properties such as sparsity and multiresolution structure.but for the CT and medical images , information need to refined for better way, So that radiologist could give the better opinion for the diagonosis

II.1 Curvlet transform based denoising*:* The curvelets are based on multiscale ridgelets combined with a spatial bandpass filtering operation. These bandpass filters are set so that the curvelet length and width at fine scale obey the scaling rule width length2. A 2-D wavelet transform is used to isolate the image at different scales and spatial partitioning is used to break each scale into blocks. Large size blocks are used to partition the large scale wavelet transform components and small size blocks are used to partition the small scale components. Finally, the ridgelet transform is applied to each block. In this way, the image edges at a certain scale can be represented efficiently by the ridgelet transform because the image edges are almost like straight lines at that scale. The Curvelet transform can sparsely characterize the high-dimensional signals which have lines, curves or hyper plane singularities.

The basic process of the digital realization for curvelet transform consist the following four stages:

1) Sub-band Decomposition: Dividing the image into resolution layers.Each layer contains details of different frequencies:

P_0 – Low-pass filter.

Δ_1, Δ_2, … ***Using Log Gabor filter to approximate the frequencies .***

The original image can be reconstructed from the sub-bands, So need to perform Sub-band decomposition

2) Smooth Partitioning: The windowing function w is a nonnegative smooth function.

3) Renormalization: Renormalization is centering each dyadic square to the unit square $[0,1]\times[0,1]$.

For each Q, the operator T_Q is defined. Before the Ridgelet Transform .The $\Delta_s f$ layer contains objects with frequencies near domain.

4) Ridgelet Analysis: Each normalized square is analyzed in the ridgelet system. The ridge fragment has an aspect ratio of $2^{-2s}\times 2^{-s}$. After the renormalization, it has localized frequency in band $[2^s, 2^{s+1}]$.A ridge fragment needs only a very few ridgelet coefficients to represent it.

III. GABOR FILTER

Gabor filters are commonly recognized as one of the best choices for obtaining localized frequency information. They offer the best simultaneous localization of spatial and frequency information. There are two important characteristics of log gabor filter. Firstly, Log-Gabor function has no DC component, which contributes to improve the contrast ridges and edges of images. Secondly, the transfer function of the Log-Gabor function has an extended tail at the high frequency end, which enables to obtain wide spectral information with localized spatial extent and consequently helps to preserve true ridge structures of images. The Gabor filter bank is a well known technique to determine a feature domain for the representation of an image. However, a Gabor filter can be designed for a bandwidth of 1 octave maximum with a small DC component in the filter. A Log-Gabor filter has no DC component and can be constructed with any arbitrary bandwidth. There are two important characteristics in the Log-Gabor filter. Firstly the Log-Gabor filter function always has zero DC components which contribute to improve the contrast ridges and edges of images. Secondly, the Log-Gabor function has an extended tail at the high frequency end which allows it to encode images more efficiently than the ordinary Gabor function .To obtain the phase information log Gabor wavelet is used for feature extraction. It has been observed that the log filters can code natural images better than Gabor filters. Statistics of natural images indicate the presence of high-frequency components. Since the ordinary Gabor filters under-represent high frequency components, the log filters is a better choice.

IV. CONCLUSION

In most of the image processing applications, a suitable noise removal phase is often required before any relevant information could be extracted from analyzed images. This Work proposes Curvelet Transformation based image denoising, which is combined with Gabor filter in place of the low pass filtering in the transform domain. For low noisy images Translation invariant wavelet based method also gives the better results but as the noise increases, all curvelet based methods outperform the wavelet based methods. An optimized Gabor filter is used to achieve edge detection of precision parts, and acquires the precise edge features through a reasonable choice to direction and scale.

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