ImageDenoising UsingContour let Transform with Application to Synthetic Aperture Radar

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Abstract:
In all methods of image denoising there is a problem always exists that is how to distinguish noise and edge. Now wavelet and contourlet are main tools in image denoising, but threshold is the key in wavelet and contourlet denoising. In order to distinguish noise and edge well, most methods in wavelet denoising are about the improvement of threshold. Aiming to resolve this problem, a new method which makes full use of the model of anisotropic receptive fields and nonsubsampled contourlet transform is proposed and it can distinguish the noise and edge effectively without the need to choose a suitable threshold. Image denoising has become an essential exercise in SAR imaging especially the satellite imaging radars. This paper proposes a SAR image denoising algorithm using contourlet transform. Numerical results show that the proposed algorithm can obtained higher peak signal to noise ratio (PSNR) than wavelet based denoising algorithms using images in the presence of gaussian noise (GN).

Keywords:nonsubsampledcontourlet; the model of anisotropic receptive fields; threshold.

1. INTRODUCTION

During the acquiring and transferring of image, there always exists noise, so in order to improve the quality of image, we must do some work to delete noise. Since eliminating noise and preserving the edge and texture detail is the main problem in image. The aim to denoise is to eliminatethe noise in the highfrequency bands, but theedge and texturedetail also lie in the high frequency.The contourlet transform is a directional multi scale transformthat is constructed by combining the Laplacian pyramid (LP) and thedirectional filter bank (DFB). Due to downsamplers and upsamplers present in both the LP and DFB, the contourlet transform is not shift-invariant. The non-subsampled contourlettransform (NSCT) is obtained by coupling anonsubsampled DFB.The idea behind a fully shift invariant multiscale directional expansionsimilar to contourlets is to obtain the frequency partitioningof Figure 1 without resorting to critically sampled structuresthat have periodically time-varyingunits such as downsamplersand upsamplers.

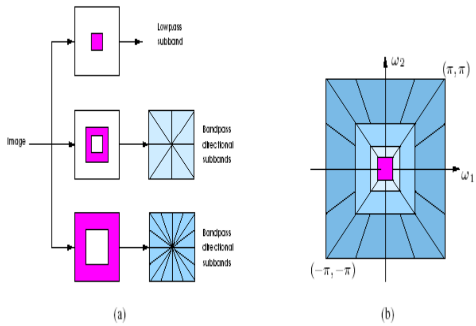


FIG 1: ThenonsubsampledContourlet transform.
(a) Nonsubsampled filter bank structure that implements the NSCT
(b) The idealized frequency partitioning

2. CONTOURLET TRANSFORM

For one-dimensional (1-D) piecewise smooth signals, like scan-lines of an image, wavelets have beenestablished as the right tool, because they provide anoptimal representation for these signals in a certain sense.In addition, the wavelet representation is amenable to efficient algorithms; in particular it leads to fast transforms and convenient tree data structures. However, naturalimages are not simply stacks of 1-D piecewise smooth scan-lines; discontinuity points (i.e., edges) are typically locatedalongsmooth curves (i.e., contours) owing to smoothboundaries of physical objects. Thus, natural images contain intrinsic geometrical structures that are key features in visual information. As a result of a separable extension from 1-D bases, wavelets in twodimensional (2-D) are good at isolating the discontinuities at edge points, but will not “see” the smoothness along the contours. In addition, separable wavelets can capture only limited directional information—an important and unique feature of multidimensional signals. These disappointing behaviours indicate that more powerful representations are needed inhigher dimensions.

Contourlet transform can offer a sparse representation for piecewise smooth images. By first applying a multiscale transform and then applying a local direction transform to gather the nearby basis function atthe same scale into linear structures. With this insight, a double filter bank structure in which at first the laplacianpyramid (LP) is used to capture the point discontinuities,And followed by a directional filter bank (DFB) to linkpoint discontinuities into linear structure.

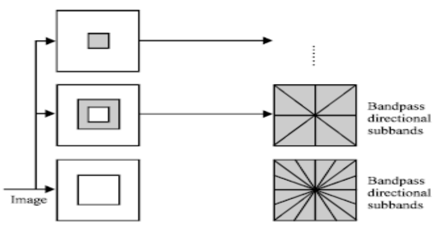
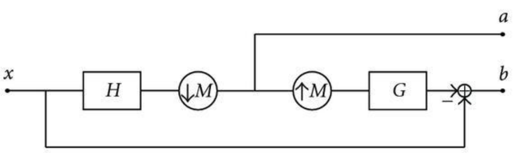


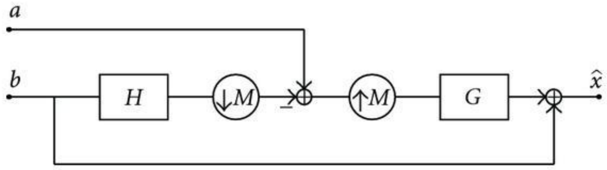
FIG: Frame work of Contourlet Transform

A. Laplacian Pyramid

The basic idea of the LP is the following. First,derive a coarse approximation of the original signal, bylowpass filtering and down sampling. Based on thiscourse version, predict the original (by up sampling andfiltering) and then calculate the difference as theprediction error. Usually, for reconstruction, the signal isobtained by simply adding back the difference to theprediction from the coarse signal. The process can beiterated on the coarse version. Analysis and usualsynthesis of the LP are shown in Figure 1.1(a) and 1.1(b),respectively. the outputs are a coarse approximation cand a difference d between the original.



(a) Analysis



(b) Synthesis

B. Directional filter bank (DFB)

Bamberger and Smith introduced a 2-Ddirectional filter bank (DFB) that can be maximallydecimated while achieving perfect reconstruction. The DFB is efficiently implemented via an-level treestructureddecomposition that leads to 2l sub bands with wedge-shaped frequency partition as shown in Figure.

The original construction of the DFB involvesmodulating the input signal and using diamond-shapedfilters. Furthermore, to obtain the desired frequencypartition, an involved tree expanding rule has to befollowed .As a result, the frequency regions for the resulting sub bands do not follow a simple ordering as shown in Figure 2 based on the channel indices. The new DFB avoids the modulation of the input image and has a simpler rule for expanding the decomposition tree. We focus on the analysis side of the DFB since the synthesis is exactly symmetric. Intuitively, the wedge-shaped frequency partition of the DFB is realized by an appropriate combination of directional frequency splitting by the fan QFB’s and the “rotation” operations done by resampling. To obtain afour directional frequency partitioning, the first twodecomposition levels of the DFB are given in Figure 3.We chose the sampling matrices in the first and secondlevel to be Q0 and Q1, respectively, so that the overallsampling after two levels is Q0Q1 = 2 · I2, or downsampling by two in each dimension.

3. THE NONSUBSAMPLED CONTOURLET TRANSFORM

The idea behind a fully shift invariant multiscale directional expansion similar to contourlets is to obtain the frequency partitioning of Figure 1 without resorting to critically sampled structures that have periodically time-varying units such as downsamplers and upsamplers. The NSCT construction can thus be divided into two parts: (1) A nonsubsampled pyramid structure which ensures the multiscale property and (2) A nonsubsampled DFB structure which gives directionality.

3.1. TheNonsubsampled Pyramid

The shift sensitivity of the LP can be remedied by replacing it with a 2-channel nonsubsampled 2-D filter bank structure. Such expansion is similar to the 1-D `*a trous*wavelet expansion and has a redundancy of J + 1 when J is the number of decomposition stages. The ideal frequency support of the low-pass filter at the j-th stage is the region [− 2j, _2j]×[− _2j , _2j]. Accordingly, the support of the high-pass filter is the complement of the low-pass support region on the [− _2j+1, _2j+1] × [−_2j−1, _2j−1] square. The proposed structure is thus different from the tensor product *a trous*algorithm. It has J + 1 redundancy. By contrast, the 2-D `*a trous*algorithm has 3J + 1 redundancy.

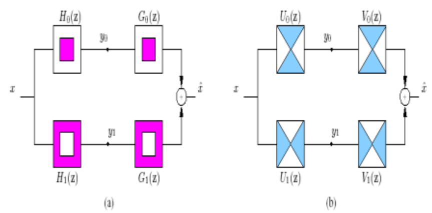
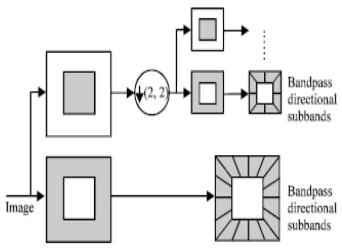


Fig2. Two kinds of desired response
(a) The pyramid desired response. (b) The fan desired response.



LP Dec Direction Dec
Fig3:The NonsubsampledContourlet

3.2. The Nonsubsampled Directional Filter Bank:

The directional filter bank is constructed by combining critically sampled fan filter banks andpre/post re-sampling operations. The result is a tree-structured filter bank which splits the frequency plane into directional wedges. A fully shift-invariant directional expansion is obtained by simply switching off the down samplers and up samplers in the DFBequivalent filter bank. Due to multirate identities, this is equivalent to switching off each of the downsamplers in the tree structure, while still keeping the re-sampling operations that can be absorbed by the filters. This results in a tree structure composed of two-channel nonsubsampled filter banks.The NSCT is obtained by carefully combining the 2-D nonsubsampledpyramid and the nonsubsampled DFB (NSDFB) .The resulting filtering structure approximates the ideal partition of the frequency plane displayed in Figure 1. It must be noted that, different from the contourlet expansion, the NSCT has a redundancy given by R =Jj=0 2lj where 2lj is the number of directions at scale j.

4. THE MODEL OF ANISOTROPIC RECEPTIVE FIELDS

In general, a high-pass filter which is in fact anOriented anisotropic LOG function in 2-D is given by

∇ 2*GD*(*x*,*y*) =*K*(2−*x*2/σ2*x*−*y*2/σ2*y*)exp−[(*x*2/(2*σ2*x*)+*y*2/(2*σ2*y*))]
Where σ *x* and σ *y* (σ *x* >σ *y*) denote the scales of x-axis y-axis respectively

5. THE NEW METHOD OF NSCT ON IMAGE DENOISE

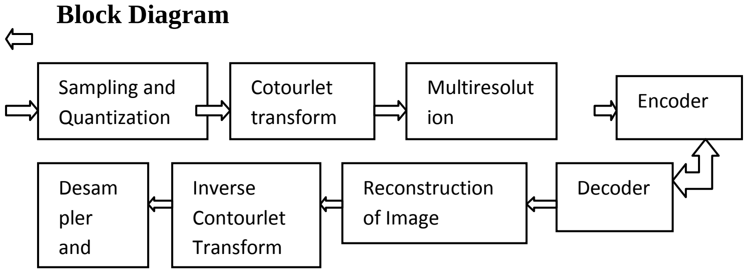
Since the NSCT can decompose image in multi-scale and multi-direction, and using the idea proposed by we know that the edge can be kept best when theanisotropic filter's long axes is in accord with the edge,and with the angle between the edge and the anisotropicfilter's long axes becomes larger the edge becomesblurrier. The DFB decomposition can be seen as the DFBfilter's long axes is placed at different orientations andwhich resulting in the many directional sub bands. Inthese directional sub bands, every one represents adirection and the edge in this direction has a largest grayscale comparing with which in any other direction sincethe edge in this direction is in accord with the filter's longaxes and the largest gray scale is denoted as the largest contourlet coefficients in corresponding position.

On the base of the idea that after the transforming of contourlet, the image contourlet coefficients is larger than the noise contourlet coefficients, we can compare thecontourlet coefficients at the same locations among thedirectional sub bands, since the largest coefficients in thesame location represent the gray scale is largest and theedge direction is in accord with the filter's long axes andwhich means the edge is kept best. Through choosing thelargest contourlet coefficients in each correspondinglocation, we choose the best kept image edge and bycomparing the contourlet coefficients the small noise coefficients are replaced by the large image edge, so itremoves the noise without the need to set a threshold.

We summarize our denoising method using the NSCT in the following algorithm:

1) Compute the NSCT of the input image for N levelsand the direction of every level can be chosen as needed.
2) As we know, the noises are in high freqency bandswhich lie in the first two or three levels, so we just need toadjust the contourletcoefficients in these first two or threelevels.For each level, we compare the directionalsubband coefficients in the same location and replace thesmall one with the large one.
3) Reconstruct the denoising image from the modifiedNSCTcoefficients,then we can get a denoised image.

Block Diagram

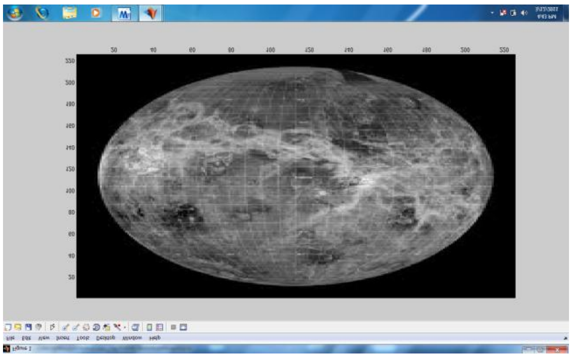


6.SYNTHETIC APERTURE RADAR

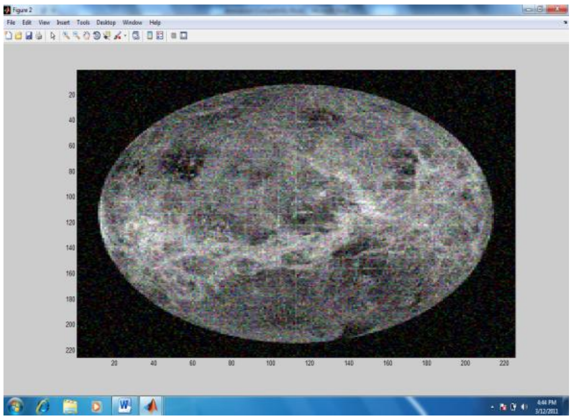
Synthetic-aperture radar (SAR) is a form of radar whose defining characteristic is its use of relative motion between an antenna and its target region to provide distinctive long-term coherent-signal variations that are exploited to obtain finer spatial resolution than is possible with conventional beam-scanning means. It originated as an advanced form of side-looking airborne radar (SLAR).

SAR is usually implemented by mounting, on a moving platform such as an aircraft or spacecraft, a single beam-forming antenna from which a target scene is repeatedly illuminated with pulses of radio waves at wavelengths anywhere from a meter down to millimeters. The many echo waveforms received successively at the different antenna positions are coherently detected and stored and then post-processed together to resolve elements in an image of the target region.

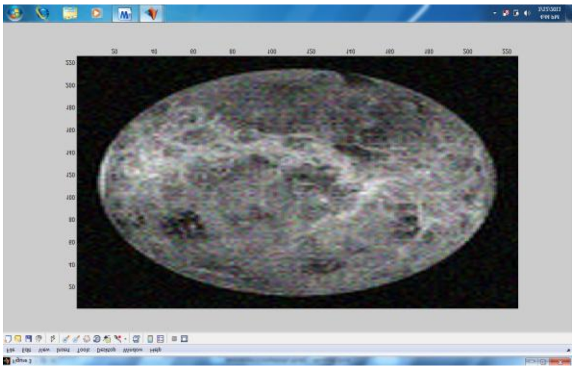
SAR images have wide applications in remote sensing and mapping of the surfaces of both the Earth and other planets. SAR can also be implemented as "inverse SAR" by observing a moving target over a substantial time with a stationary antenna.



Original Input Image



Noisy Image



Denoised Image

7. NUMERICAL EXPERIMENTS

We compare the denoising results by the proposedalgorithm with the wiener filter. In the experiments, wechoose a Lena (256*256) to testify our method. Fig7shows the results. Fig a) represents the ideal image, Fig b)represents the image added gauss noise and Fig c) showsthe wiener filtering image and Fig d) shows the result ofour approach. From these figures we can see that wienerfiltering image has more noise and the edge and featuredetail is blurry. And the result of our approach has lessnoise and the edge is kept well. Several noise images aretested to improve the effects, and the results are listed in

8. CONCLUSION

In this article, we use the idea that the edge can be keptbest when the anisotropic filter's long axes is in accordwith the edge, and with the angle between the edge andthe anisotropic filter's long axes becomes larger the edgebecomes blurrier in nonsubsampledcontourlet transformand propose a new contourletdenoise technology that caneliminate noise effectively and preserve the edge wellwithout the effort to set a threshold. From the figures andthe data in the table 1, we can see that our approach is super to wiener filter in visual and PSNR.

9. REFERENCES

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