TWO-LAYERED IMAGE COMPRESSION USING 2G BANDELETS AND WAVELETS[1]

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Abstract An image can be decomposed into the structural component and the geometric textural component. Based on this idea, an efficient two-layered compressing algorithm is proposed, which uses 2nd generation bandelets and wavelets. First, an original image is decomposed into the structural component and the textural component, and then these two components are compressed using wavelets and 2nd generation bandelets respectively. Numerical tests show that the proposed method works better than the bandelets and JPEG2000 in some specific SAR scene.

Key words Bandelets; Wavelets; Total Variation (TV)

CLC index TN957

DOI 10.1007/s11767-007-0171-4

I. Introduction

The wavelet transform has achieved great success in image compression over the last ten years. It is more powerful than Fourier analysis when coding point singularity in one-dimensional situation. However, most two-dimensional wavelet coders in use are separable filter banks that are tensor product of one dimensional wavelet transform. They cannot take advantage of the higher dimensional singularity (*i.e.*, geometrical edge) of the image structures mainly due to the lack of directions of the bases of the wavelet transform. So the wavelet transform is an optimal tool when only capturing zero dimensional singularity or processing uniform regions.

Pennec and Mallat proposed the 1st Generation (1G) bandelets[1], which are constructed from geometric flows of vectors indicating the local directions where the image gray levels have regular variations. Unfortunately, the 1G bandelets are not built directly in the discrete domain, and they do not provide a multi-resolution representation of the geometry. In consequence, the implementation and the mathematical analysis are more involved and less efficient[2]. In Ref.[3], the 2nd Generation bandelets (2G bandelets) was introduced. The 2G bandelets solve the above problems, and show excellent performance in capturing higher dimensional singularity.

Although the 2G bandelets can approximate geometrical regularity effectively and outperform wavelet codec in image compression, but the computing complexity and the compression efficiency are not satisfactory. A better solution is to combine the advantages of 2G bandelets and wavelets. In this letter, we propose a novel image compression method based on wavelets and 2G bandelets. First, we decompose an original image f into u and v, where u represents the structural component and v the texture component. And then the two components are compressed by wavelets and 2G bandelets respectively. Numerical results showed that the proposed method outperforms singular the bandelets and JPEG2000 compression system.

II. Image Decomposition

The general concept is that an image can be composed by a structural part u which corresponds to the main large scale smooth regions, and a texture part v which contains the geometrical small-scale-details, usually with some periodicity and oscillatory nature[4,5].

Recently, image decomposing models based on Total Variation (TV) regularization methods become more and more popular[6]. The TV-L^1[7] algorithm we adopt in this article decomposed an image f into a component u belonging to Banach Varia-

[1] Manuscript received date: September 19, 2007; revised date: March 10, 2008.

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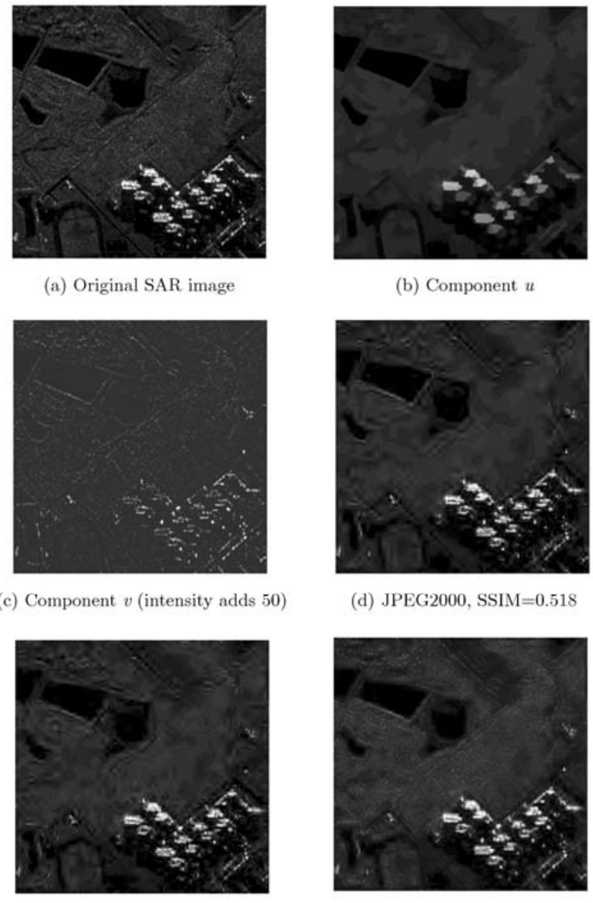
tion (BV) Space and a component v in L^1, where L^1 is Lipschitz Space. In the algorithm, the following expression is minimized:

$$\underset{(u,v)\in \mathrm{BV}\times L^1 / f=u+v}{\mathrm{Min}} \left(\int | Du | + \lambda \, || v ||_{L^1} \right) \quad (1)$$

where $\int | Du |$ is the total variation of u. The parameter λ controls the energy ratio of u and v. In fact, the smaller the λ is, the less information v contains, and therefore the more u is averaged. In the experiments, we set λ to 0.8, and the result of decomposition of the test image (256×256) is shown in Fig.1, where Fig.1(b) is the structural component and Fig.1(c) is the textural component.



(a) Original SAR image (b) Component u

(c) Component v (intensity adds 50) (d) JPEG2000, SSIM=0.518

(e) Bandelets, SSIM=0.579 (f) The proposed method, SSIM=0.681

Fig.1 SAR image decomposition and compression results at 0.2bpp

III. Two-layered Image Compression

In Section II, we decompose the original image f into the structural component u and the textural component v. In this section, we will compress the two parts using a two-layered strategy. First we compress u with wavelets, and then compress v based on 2G bandelets.

1. Structural component compression using wavelets

The structural component u obtained from f is made up of many uniform regions, where the grey level of pixels stays largely identical. For this kind of smooth image, the optimal compression method is wavelets, which can achieve both low bit-rate and high visual quality.

We choose Daubechies 9/7 lifting wavelets filter to compress u. Great numbers of coefficients should be preserved to approximate geometrical edges in images using wavelet transform. The u component is smooth so that it is more suited to be compressed with wavelet codec than the textural component. Then the coarse representation is an approximation of u and also a compressed version of it with some distortion. The process can be repeated with the average component of u being the input to the next stage till the number of samples reduces to one. This last sample represents the average component of the entire u. The total number of coefficients after the transform equals the number of coefficients before the transform.

Different from bandelets, which process u and v component with the same strategy, our method compress u with wavelet transform. Consequently, our processing speed is faster and memory allocation is smaller.

2. Texture compression using 2G bandelets

The textural part v contains most of high frequency information of the original image, such as edges, curves, contours and so on. Due to the flexible, anisotropic and multi-directional basis, bandelets are the right tool to capture and approximate these high dimensional singular objects.

2G bandelets construct their adaptive basis from discrete orthogonal wavelet basis[8]. There are two stages in 2G bandelet transform: a two-dementional (2D) warped wavelet transform stage with a sub-band filtering along the geometrical flow lines in the image, and a bandeletization stage that transforms the warped wavelet coefficients to compute bandelet coefficients along the geometrical flow lines.

Computing the best directions of geometrical flows and quadtree segmentation in each subband of wavelets are time-consuming. The v component contains mainly the high frequency information such as the edges and contours. To reduce the time and memory of the quadtree segmenting process, we adopt the following three steps to improve the performance of the 2G bandelets:

(1) Only three levels decomposition is preformed to the v component, then we get high frequency sub-bands: ($HL_0/LH_0/HH_0$), ($HL_1/LH_1/HH_1$) and ($HL_2/LH_2/HH_2$), and the coefficients of the low frequency sub-band would nearly all be zeros;

(2) Only the ($HL_0/LH_0/HH_0$) of the first levels is chosen to perform quadtree segmenting to get the best quadtree segmention, and obtain the directions of geometrical flows;

(3) For the 2nd and the 3rd level, only the HL_1 and HL_2 are chosen to perform quadtree segmention.

IV. Numerical Experiments

In this section, the compression results using JPEG2000, 2G bandelets and the proposed method are compared. We exhibit their performance difference not only through subject visual effect but also SSIM (Structural SIMilarity)[9] image quality assessment system, and analyze the experimental results.

1. SSIM assessment system

The SSIM index is a novel method for evaluating the similarity between the reconstructed image and the original image. It is an improved criterion for image quality evaluation compared with the MSE (Mean Squared Error) and PSNR (Peak Signal to Noise Ratio). SSIM is defined as:

$$\mathrm{SSIM}(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma} \qquad (2)$$

where $l(x,y)$ is the luminance comparison, $c(x,y)$ is the contrast comparison, and $s(x,y)$ is the structure comparison.

The value of SSIM (x, y) should be between 0 and 1. The higher the value of SSIM (x, y) is, the more similar the images x and y are. If SSIM (x, y) = 1, x and y are the same images.

2. Experimental results and analysis

Fig.1 is a SAR image compressed using three different methods at the bit-rate of 0.2bpp. Comparing the reconstructed image under each compression methods, we can see that the JPEG2000 compression system suffers the loss of high frequency information. As showed in Fig.1(d), the detailed texture of the farmland and stadium is blurry and ring effect occurs in these areas.

The bandelets can preserve the image textural details better than JPEG2000, but it also produces some pseudo edge-like regions (that is, the gray gradient varying regions are taken as marginal textural regions), so the visual effect of the reconstructed image is not very good.

The method proposed in this letter can basically retain the basic structural information and rich textural information, and effectively restrained the pseudo-edge region. Tab.1 is the SSIM under different bit-rate of these three compressing methods. From the table we can see that at low bit rates, the proposed method can obtain higher SSIM values than that using JPEG2000 and bandelets.

Tab.1 SSIM values at different bit-rates

Bit-rate(bpp)	SSIM		
	JPEG2000	Bandelets	The proposed method
0.15	0.475	0.595	0.711
0.30	0.670	0.752	0.803
0.50	0.812	0.847	0.861
0.70	0.879	0.898	0.905
1.00	0.915	0.917	0.922

Wavelet transform is the basic operation of JPEG2000 method. As we know, for the image texture and edge contour, the wavelet transform is not the best sparse expression tool. At low bit-rate, the loss of the high-frequency band coefficient will inevitably lead to ring effects. The bandelets have strong ability on capturing the high-dimensional information, but it is unable to identify whether the region with varying gray is corresponding to the object contour. Hence its reconstructed image will have pseudo-edge region, which would affect the visual effects of the image. The proposed method combines the advantages of both the wavelet transform and bandelets. Image decomposition is the key issue of the whole compressing framework. The gray gradually varying region is removed from the textual component to improve the performance of the bandelets, and the detailed textural information is removed from the structural component to satisfy the wavelet codec, which avoids the limitation when being used separately.

V. Conclusion

In this letter, we propose a new image compression method that combines image decomposition, wavelets and 2G bandelets together. It makes full use of the advantages of wavelets and 2G bandelets. As a result, it can not only capture the geometrical regularities in images efficiently, but also achieve higher compression-ratio and better visual effect compared with wavelets or bandelets. The experimental results show that the proposed method is an effective scheme for SAR image compression.

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