

Contourlet Based Image Recovery and De-noising Through Wireless Fading Channels

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Abstract –

The contourlet transform consists of two modules: the Laplacian Pyramid and the Directional Filter Bank. When both of them use perfect reconstruction filters, the contourlet expansion and reconstruction is a perfect dual. Therefore, the contourlet transform can be employed as a coding scheme. The contourlet coefficients derived above can be transmitted through the wireless channel in the same way as transmitting the original image, where the transmission is prone to noise and block loss. However, the reconstruction at the receiver performs differently if the image is transmitted directly or coded by the contourlet transform. This paper studies the performance of the contourlet coding in image recovery and denoising. The simulation results show that for general images the contourlet transform is quite competitive to the wavelet transform in the SNR sense and in visual effect. Further, the contourlet transform can be used in a wireless face recognition system to extract the unique feature that other transforms can not discover, For face recognition system, the recovery of the original image is not essential any more; therefore, the resources on the image reconstruction from the contourlet coefficient can be saved.

Key words: Contourlet, Wireless, Face recognition system, Wavelet

I INTRODUCTION

The wavelet transform has been widely used in image compression and denoising. In image compression, the wavelet transform produces much less blocking artifacts

than the DCT under the same compression ratio; thus as the DCT was used in JPEG when the DCT was the state of the art image compression technique during the era of JPEG, the wavelet is adopted in JPEG2000. The wavelet transform also performs quite well in image de-noising. In particular, the stationary wavelet transform (SWT) [5] and the translation invariant wavelet transform (TIWT) [6] produce smaller mean-square-errors than the regular wavelet transform, and the SWT or TIWT based image reconstruction are perceptually more delicate and smoother with much less observable artifacts than the regular wavelet transform. However, the 2D wavelet transform used in image processing is, intrinsically, a tensor-product implementation of the 1D wavelet transform; therefore it does not work well in retaining the directional edges in the images, and it is not efficient in representing the contours not horizontally or vertically.

As an attempt to represent the curves more efficiently, Starck, Candes and Donoho developed the continuous curvelet transform [4] in polar coordinates. The curvelet transform uses the directional filter bank to capture the directional curvature information, and it is proved mathematically that the continuous form of the curvelet transform is rotation invariant and the expansion to the curvelet transform can produce perfect reconstruction. But the implementation of the curvelet transform in the discrete form is not a trivial issue. Starck, Candes and Donoho further proposed a polar sampling scheme and then interpolating the samples onto the rectopolar grid. This Cartesian-to-rectopolar conversion is theoretically reversible; therefore the perfect reconstruction property should be retained. However, in practice, the complex polar sampling is usually simplified by nearest neighbor substitution, and the mathematical properties may not be preserved.

Then M. N. Do and M. Vetterli developed the contourlet in the discrete form [1], which is defined on the regular grids instead of the polar coordinate and more “digital-friendly”. Another difference between the contourlet and the curvelet is that the contourlets have the 2D frequency partition on the centric-squares, but the curvelets have the 2D frequency partition on the centric-circles. The contourlet construction provides a space-domain multiresolution scheme that offers flexible refinement for both the spatial resolution and the angular resolution.

In short, the contourlet transform is an efficient directional multiresolution image representation, which differs from the wavelet transform in that the contourlet transform uses non-separable filter banks developed in the discrete form; thus it is a true 2D transform, and it overcomes the difficulty in exploring the geometry in digital images due to the discrete nature of the image data.

As to the applications of the contourlet transform, Ramin Eslami and Hayder Radha [3] once revised it by cycle spinning based techniques for image denoising. This could be used to denoise the received images at the end of the wireless channel.

In contrast, this paper uses the contourlet transform as a coding scheme for images. Namely it’s the contourlet coefficients that are transmitted through the wireless fading channel. For comparison, the wavelet based transform is also considered, and the simulation shows that the MSE and the visual effect for both the contourlet transform and the wavelet transform are quite close. Nevertheless in the MSE sense, if the image includes lots of edges, the contourlet transform performs better at retaining this edge information; but if the image is relatively smooth or monotonic, the contourlet transform tends to overshoot and therefore the wavelet transform performs better.

This paper has an application scenario in the wireless face recognition system. The data transmitted within the network may be the original images or the compressed/encoded coefficients by wavelets or contourlets. The reason of selecting the contourlet transform is two folded: The first one is for the progressive

data compression/expansion when transmitting/receiving the more significant coefficients with higher priority. The second one is for the better image reconstruction in the wireless environment.

II. THE CONTOURLET TRANSFORM

The contourlet transform is a true 2D transform defined in the discrete form to capture the contour information in all directions; therefore it’s very suited for image processing.

The first question in concern is what are the properties of the contourlet transform. This can be comprehended by comparing the contourlet transform with the widely used wavelet transform. Their difference is intuitively illustrated by Figure.1 on next page, which is taken from paper [1].

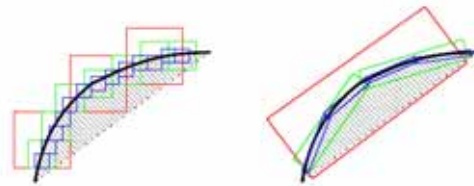


Figure. 1 Wavelet v.s. Contourlet

The idea of the wavelet transform (on the left) is to use the square shaped brush strokes along the contour to paint the contour, with different brush sizes corresponding to the multi-resolution structure of the wavelets. As the resolution becomes finer, the wavelet transform must use many fine “dots (small squares)” to capture the contour. On the other hand, the contourlet transform (on the right) uses different elongated shapes in a variety of directions following the contour to paint the contour with more flexibility. The contourlet transform uses contour segments to realize the local, multi-resolutional and directional image expansion; hence it’s named the contourlet transform. The efficiency of a representation is defined as the ability of it to capture the information of an object in interest using fewer descriptors. [1] shows that with parabolic scaling and sufficient directional vanishing moments, the contourlets achieve the optimal

approximation rate for a 2D piecewise smooth functions with twice continuously differentiable contours. In contrast, even though with dyadic scaling and sufficient vanishing moments, the wavelets can approximate any twice continuously differentiable 2D functions with arbitrary accuracy, the efficiency of the wavelet transform may not be as high as the contourlet transform if the contour is not horizontally or vertically, as shown in the illustration example of Figure.1.

The second question in concern is how to implement the contourlet transform. Conceptually the contourlet transform first utilizes a wavelet-like transform for edge detection such as the Laplacian pyramid, and then the contourlet transform utilizes a local directional transform for contour segment detection such as the directional filter bank to link point discontinuities into linear structure. Therefore contourlets may have elongated supports at various scales, directions and aspect ratios. There are some variations or improvements on these two steps. For instance, in step 1, paper [1] used the pseudo inverse structure for reconstruction, which is more robust in the presence of noise; and then in step 2, paper [1] simplified the traditional directional filter bank by first shearing the image by certain angles and then passing the sheared image through two fan filters, one for vertical direction and one for horizontal direction. The shearing to multiple angles and then filtering by vertical/horizontal filters is equivalent to the directional filter bank. What's more, all transforms in shearing and filtering are done directly on the discrete grid. Therefore the contourlet transform is a true 2D digital image transform. The implementation of the contourlet transform is summarized in Figure. 2, which is reproduced from [1].

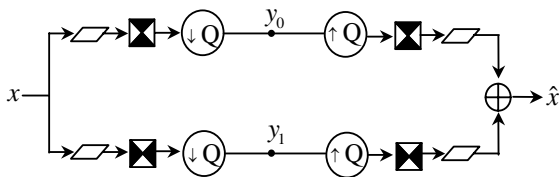


Figure. 2 Expansion to the contourlets and reconstruction from the contourlets

In Figure. 2, the parallelogram represents the shearing operator, the quincunx represents the vertical or horizontal filter, and the circle with Q inside represents downsampling or upsampling. The left half is to expand the image by the contourlet transform and the right half is the reconstruction. In multi-resolution analysis, such process can be done iteratively to realize the multi-scale and multi-direction expansion or reconstruction.

III. WIRELESS FADING CHANNEL

As reviewed in II, the contourlet transform is efficient in capturing the contour information, which is a prominent feature that is good to keep in image processing. [3], [4] and other papers in denoising assume x in Figure. 2 to be the noise-contaminated images such as the ones received at the end of a wireless channel, and then hard-threshold the y_0 and y_1 to reconstruct \hat{x} , which is a denoised estimation of the original image.

In this paper, a different application of contourlet is discussed, which encodes the images into contourlet coefficients and then transmit the contourlet coefficients through the wireless channel instead of transmitting the whole original images. In particular, the left half of Figure. 2 is implemented in the transmitter (Tx), and the right half of the Figure. 2 is implemented in the receiver (Rx) as shown in Figure. 3. The effect of the fading channel (Ch) is to distort the y_0 and y_1 in Figure. 2 to be the \tilde{y}_0 and \tilde{y}_1 in Figure. 3.

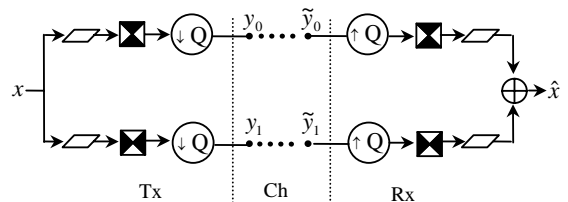


Figure. 3 Contourlet transform used in wireless image transmission

At the receiver end, the reconstruction directly from the received coefficients is a simple recovery of the original image. If the received coefficients are hard

thresholded or processed by other more delicate denoising schemes, the reconstructed image is a denoised one.

The wireless channel is assumed to be Rayleigh flat and slow fading. The transmission system is without any diversity compensation; the improvement by the diversity schemes such as selective combining, maximum ratio combining and equal gain combining may be discussed in later papers. The path loss is neglected here because the wireless face recognition system is usually distributed in a relatively small local area; the equipments are assumed to be fully powered to be able to communicate within the boundary of the network. Therefore, the variation of such a wireless network is mainly due to the small scale fading.

In short, the envelope of the fading channel is Rayleigh distributed with following pdf:

$$f_r(R) = \frac{R}{\sigma^2} e^{-\frac{R^2}{2\sigma^2}} \cdot u(R) \quad (1)$$

Where R is the envelope, $\sqrt{2}\sigma$ is the RMS of R (notice that $E(r^2) = 2\sigma^2$). $u(\cdot)$ is the step fun to indicate that the envelope is nonnegative.

The dashed line in Figure. 3 is now detailed in Fi 4 with r as the multiplicative Rayleigh envelope ar as the AWGN.

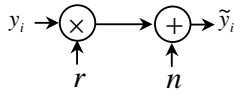


Figure. 4 Wireless channel model ($i = 0,1$)

IV. IMAGE RECOVERY AND DENOISING

Without noise or distortion, the reconstruction from the transform expansion by both the contourlets and the discrete wavelets are perfect with zero MSE.

However, due to the fading channel, the image recovery from the distorted coefficients may not be perfect any more. In order to show the performance of this contourlet based encoding scheme, a comparison with the wavelet transform is conducted.

1. Expand the image into its wavelet coefficients, and transmit its wavelet coefficients through the wireless channel. This scheme may vary when selecting different wavelet transform and different levels. Here the Daubechies 4 wavelet is used for its better approximation ability to curvature structure. The expansion level is 2 for simplicity.
2. Expand the image into its contourlet coefficients, and transmit its contourlet coefficients through the wireless fading channel.

The second scheme is what this paper proposed. The contourlet transform is repacking the information in the original image into a more compact form with most of the coefficients close to zero and only a small portion of the coefficients being significant.

The resultant recovered images without any denoising are shown in Figure. 5.



Figure. 5. (a) Original Image
(b) Reconstructed Image by scheme 1 based on contourlet transform
(c) Reconstructed Image by scheme 2 based on wavelet transform.

The image has size 256x256 and 256 gray levels. The MSE for (b) is 46.280704 and the MSE for (c) is 55.446824. The two MSEs are relatively close. Visually, the contourlet transform based reconstruction has some “scratches” that is due to the misrepresentation of the contourlet in that region. The wavelet transform based reconstruction has some missing “dots”, which looks like salt and pepper.

The distorted coefficients can be used to estimate the true coefficients by the following denoising schemes, where γ is the constant to weigh the received value to estimate the true value.

1. Hard thresholding

$$\gamma_j = 1(|\hat{\alpha}_j(x)| > t\sigma) \quad (2)$$

Where t is certain threshold, σ is the noise variance, $1(x) = 1$. It is shown in Figure. 6.

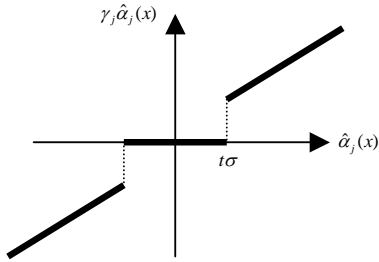


Figure .6 Hard Thresholding

2. Soft thresholding

$$\gamma_j = (1 - t\sigma / |\hat{\alpha}_j(x)|)_+ \quad (3)$$

Where $(x)_+ = x$, if $x > 0$. It is shown in Figure. 7.

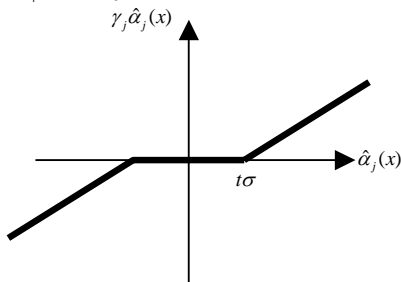


Figure. 7 Soft Thresholding

3. Stein's thresholding

$$\gamma_j = (1 - t\sigma / |\hat{\alpha}_j(x)|^2)_+ \quad (4)$$

It is shown in Figure. 8.

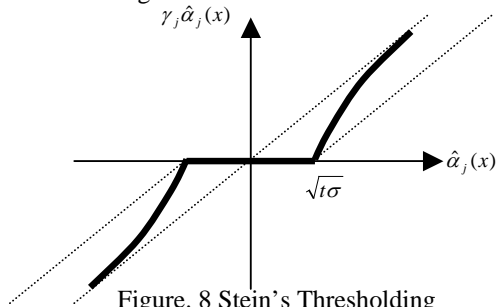


Figure. 8 Stein's Thresholding

The hard thresholding keeps the received value of the large coefficients, but it's not continuous. The soft thresholding is continuous, but there's always a bias between the estimated value and received value. The Stein's thresholding is a compromise between the two schemes to be both continuous and unbiased for the large coefficients. Therefore the simulations are done with the Stein's thresholding scheme.

The resultant denoised images corresponding to Figure. 5 are shown in Figure. 9.



Figure. 9. The denoised image from Figure. 5 by Stein's thresholding. (a) Original Image (b) Denoised by Stein's thresholded contourlet coefficients (c) Denoised by Stein's thresholded wavelet coefficients

The contourlet based reconstruction is remedied by the Stein's thresholding effectively, and the curves on the face image looks smooth. The wavelet based reconstruction is remedied by the Stein's thresholding to a certain extent, as can be seen from the fact that the "salt and pepper" is more sparse than before. But there's still a bright "salt" quite visible. The MSE for (b) is now 25.325113, and the MSE for (c) is now 32.522570.

V. Wireless Face Recognition System

Based on the results in section IV, it can be seen that the contourlet transform is a unique transform to derive the intrinsic features of the face images. In addition to encoding the images for transmission, the contourlet transform can be also used as a feature extractor in face recognition system.

Face recognition system is a very important component of biometric security system for its speed, non-contacting

property and its increasing accuracy. Wirelessly constructed face recognition system will be more flexible in watching the dynamic region of interest, in the specific deployment of cameras and in sharing the face database. In wired face recognition system, the data transmission is usually more reliable. Therefore the goal of a successful wireless face recognition system is to approach the performance of a wired system while keeping the convenience of a wireless system. What's more, with the flexibility of the wireless system, wireless structure may improve the configuration of the system, and thus improve the face recognition rate. The difficulty in the wireless face recognition system is to overcome the transmission noise and block loss due to fading.

The experiment is simulated on the ORL face database with 40 subjects each with 10 face images. When using 20 subjects as the registered users, the 1st-ranking detection rate of the registered users by the contourlet transform in the wireless system is the same as the wired system at 94%. This means that 94% of the correct decisions are within the first possible match.

SUMMARY

This paper utilized the contourlet transform as a coding scheme to expand the images into contourlet coefficients for transmission through the wireless fading channel. Several denoising schemes are implemented to denoise the received coefficients and the resultant images have less MSE than simple reconstruction. The contourlet denoising is also competitive to the wavelet denoising. In the example shown in Figure. 5 and 8, the face image has wrinkles, which is represented by the contourlets more efficiently; therefore the contourlet performs better in denoising both in MSE sense and visually. Further the application of contourlet transform in wireless face recognition system is also discussed. The detection rate of both the wireless system and the wired system, with only the transmission channel being different, is 94%. Therefore the application of the wireless face recognition is applicable, and it is more flexible and more cost effective.

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<http://www.ifp.uiuc.edu/~minhdo/software/>

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