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AN EFFICIENT TECHNIQUE FOR DIRECTIONAL MULTI RESOLUTION IMAGE USING CONTOURLET TRANSFORM

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Abstract

The limitations of commonly used separable extension of one-dimensional transforms, such as the Fourier and wavelet transforms, in capturing the geometry of image edges are well known. In this project we pursue a true two dimensional transforms that can capture the intrinsic geometrical structure that is key in visual information. The main challenge in exploring geometry in images comes from the discrete nature of the data. Thus, unlike other approaches, such as curvelet, that first develop a transform in the continuous domain and then discretize for sampled data, our approach starts with a discrete domain construction and then studies its convergence to an expansion in the continuous domain. Specifically, we construct a discrete domain multiresolution and multidirection expansion using non-separable filter banks, in much the same way that wavelets were derived from filter bank. This construction results in a flexible multiresolution, local, and directional image expansion using contour segments, and, thus, it is named the contourlet transform. The discrete contourlet transform has a fast iterated filter bank algorithm that requires an order N operations for N- pixel images. Furthermore, we establish a precise link between the developed filter bank and the associated continuous-domain contour let expansion via a directional multiresolution analysis framework. We show that with parabolic scaling and sufficient directional vanishing moments, contourlet achieve the optimal approximation rate for piecewise smooth functions with discontinuouities along twice continuously differentiable curves. Finally we show some numerical experiments demonstrating the potential of contourlets in several image processingapplications

Introduction

Efficient representation of visual information lies at the heart of many image processing tasks, including compression, denoising, feature extraction, and inverse problems. *Efficiency* of a representation refers to the ability to capture significant information about an object of interest using a small description. For image compression or content-based image retrieval, the use of an efficient representation implies the compactness of the compressed fileor the index entry for each image in the database.

IMAGE CONTOURS

However, natural images are not simply stacks of 1-D piecewise smooth scan-lines; discontinuity points (i.e. edges) are typically located along smooth curves (i.e. contours) owing to smooth boundaries 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 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 behaviors indicate that more powerfulrepresentations are needed in higher dimensions.

IMAGE DIGITIZATION

An image captured by a sensor is expressed as a continuous function f(x, y) of two coordinates in the plane Image digitization means that the function f(x, y) is sampled into a matrix with m rows and n columns. The image quantization assigns to each continuous samples an integer value. The continuous range of image functions f(x,y) is split into k intervals. 0The finer the sampling (i.e. the larger m and n) and quantization (larger k) the better the approximation of the continuous image f(x, y)

SAMPLING AND QUANTIZATION

To be suitable for computer processing an image function must be digitized both spatially and in amplitude. Digitization of spatial coordinates is called image sampling and amplitude digitization is called gray level quantization.

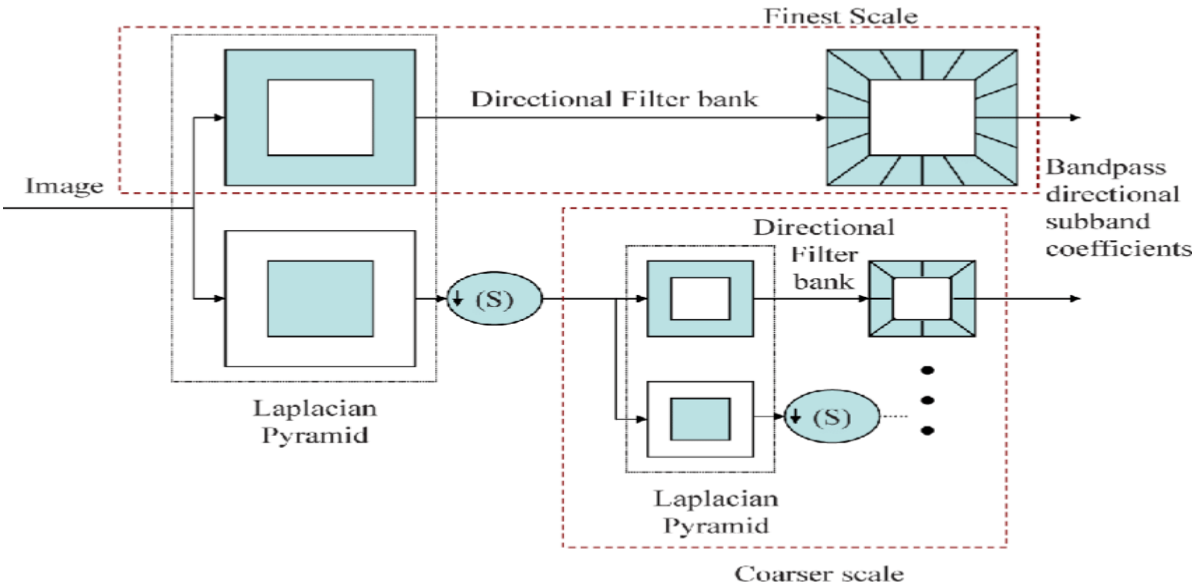
IMAGE PROCESSING

The field of digital image processing refers to processing of digital image by means of a digital computer. A digital image is an image f(x , y) that has been discretized both in spatial coordinates and brightness. A digital image can be considered as a matrix whose row and coloumn indices identifies a point in the image and corresponding matrix element value identifies the gray level at that point. The elements of such a digital array are called image elementd, picture elements, pixels or pels. The last two being commonly used abbreviations of "pictures elements".

Proposed Work

As we know 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 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 behaviors indicate that more powerful representations are needed in higher dimensions. In this project, we proposed a *double filter bank* structure for obtaining sparse expansions for typical images having smooth contours. In this double filter bank, the Laplacian pyramid is first used to capture the point discontinuities, and then followed by a directional filter bank to link point discontinuities into linear structures. The overall result is an image expansion using basic elements like contour segments, and thus are named *contourlets*. In particular, contourlets have elongated supports at various scales, directions, and aspect ratios. This allows contourlets to efficiently approximate a smooth contour at multiple resolutions in much the same way as the new scheme. In the frequency domain, the contourlet transform provides a multiscale and directional decomposition.

Block Diagram



Laplacian pyramid:

Let $g0(ij)$ be the original image, and $g1(ij)$ be the result of applying an appropriatelow-pass filter to g0. The prediction error $L0(ij)$ is then given by

$$L0(ij) = g0(ij) - g1(ij)$$

Rather than encode $g0$, we encode $L0$ and $g1$. This results in a net data compression because

a) $L0$ is largly decorrelated, and so may be represented pixel by pixel with many fewer bits than $g0$, and b) $g1$ is low-pass filtered, and so may be encoded at a reduced sample rate. Further data compression is achieved by iterating this process.

The reduced image $g1$ is itself low-pass filtered to yield $g2$ and a second error image is obtained: $L2(ij)=g1(ij)-g2(ij)$.

By repeating these steps several times we obtain a sequence of two-dimensional arrays $L0, L1, L2, \ldots, Ln$. In our implementation each is smaller than its predecessor by a scale factor of 1/2 due to reduced sample density. If we now imagine these arrays stacked one above another, the result is a tapering pyramid data structure. The value at each node in the pyramid represents the difference between two Gaussian-like or related functions convolved with the original image. The difference between these two functions is similar to the "Laplacian" operators commonly used in image enhancement. Thus, we refer to the proposed compressed image representation as the Laplacian-pyramid code.

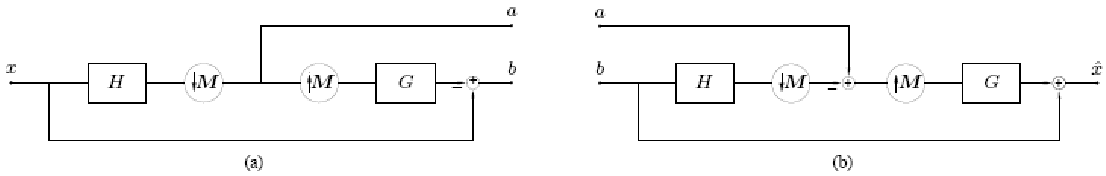


Figure 3.1 :Laplacian pyramid. (a) One level of decomposition. Theoutputs are a coarse approximation a[n] and a difference b[n] between the original signal and the prediction. (b) The new reconstruction scheme for the Laplacian pyramid.

Recall that our purpose for constructing the reduced image $g1$ is that it may serve as a prediction for pixel values in the original image $g0$. To obtain a compressed representation, we encode the error image which remains when an expanded $g1$ is subtracted from $g0$. This image becomes the bottom level of the Laplacian pyramid. The next level is generated by encoding $g1$ in the same way. We now give a formal definition for the Laplacian pyramid, and examine its properties. *Laplacian Pyramid Generation* The Laplacian pyramid is a
sequence of error images $L0$, $L1$, ..., LN. Each is the difference between two levels of theGaussian pyramid. Thus, for $0 < 1 < N$,

$Ll = gl$ – EXPAND $(gl + 1) = gl — gl + 1$. 1.

Since there is no image $gN + 1$ to serve as the prediction image for gN, we say $LN = gN$.

3.3 Directional filter bank:

The DFB realizes a division of 2-D spectrum into 2n wedge shaped
slices as shown in Fig using an n-levels iterated tree structured filter banks. The method is touse appropriately thequincunx filter bank (QFB) together with modulations and rotations.

Rotations in DFB are achieved by *resampling* matrices Ri (that is, matrices with determinantequal to +-1, so they represent a rearrangement of the input samples).

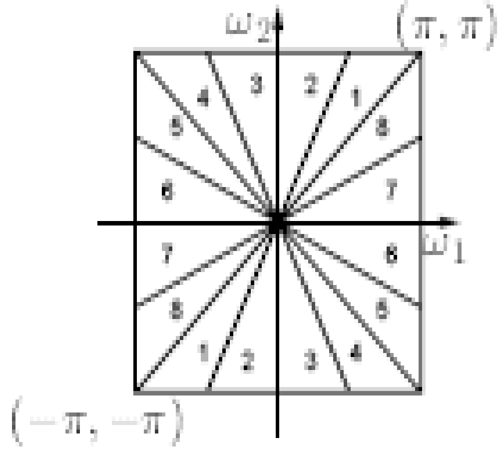
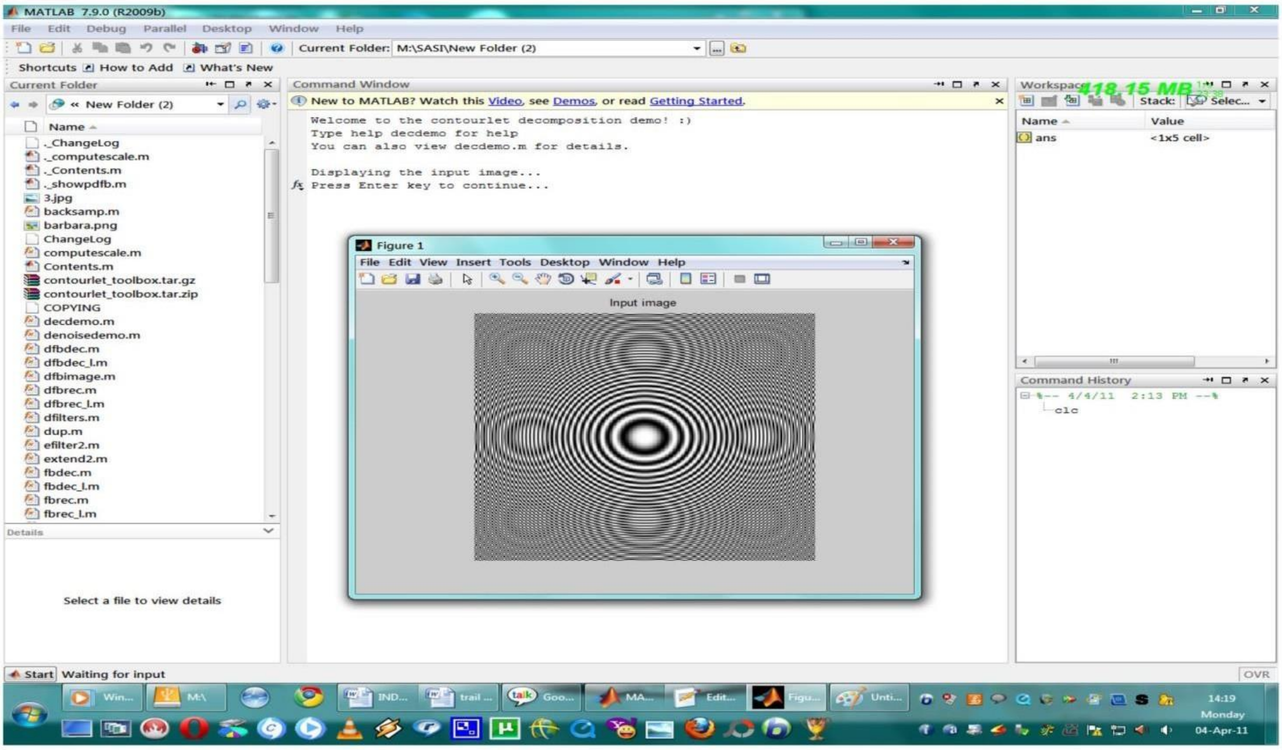


Figure 3.2. Directional filter bank frequency partitioning

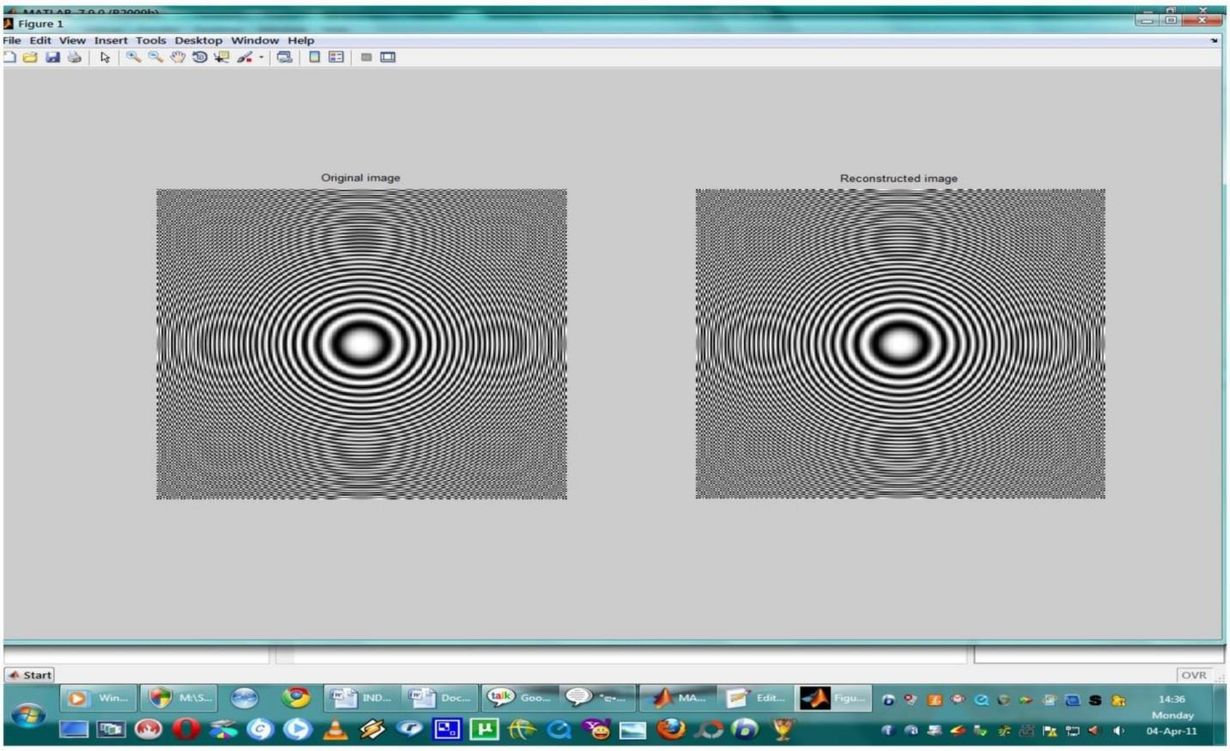
More specifically, the blocks in the binary decomposition tree of the DFB are made up from two extensions of the QFB: the modulated QFB and the “skewed” QFB’s , the former one is used at the first two levels, while the later one is used at the remaining levels. Therefore, it can be shown that the DFB is perfect reconstruction (PR) or orthogonal *if and only if* its kernel QFB is PR or orthogonal, respectively. As a result, the design of DFB essentially amounts to the design of QFB with the desired properties.

Results

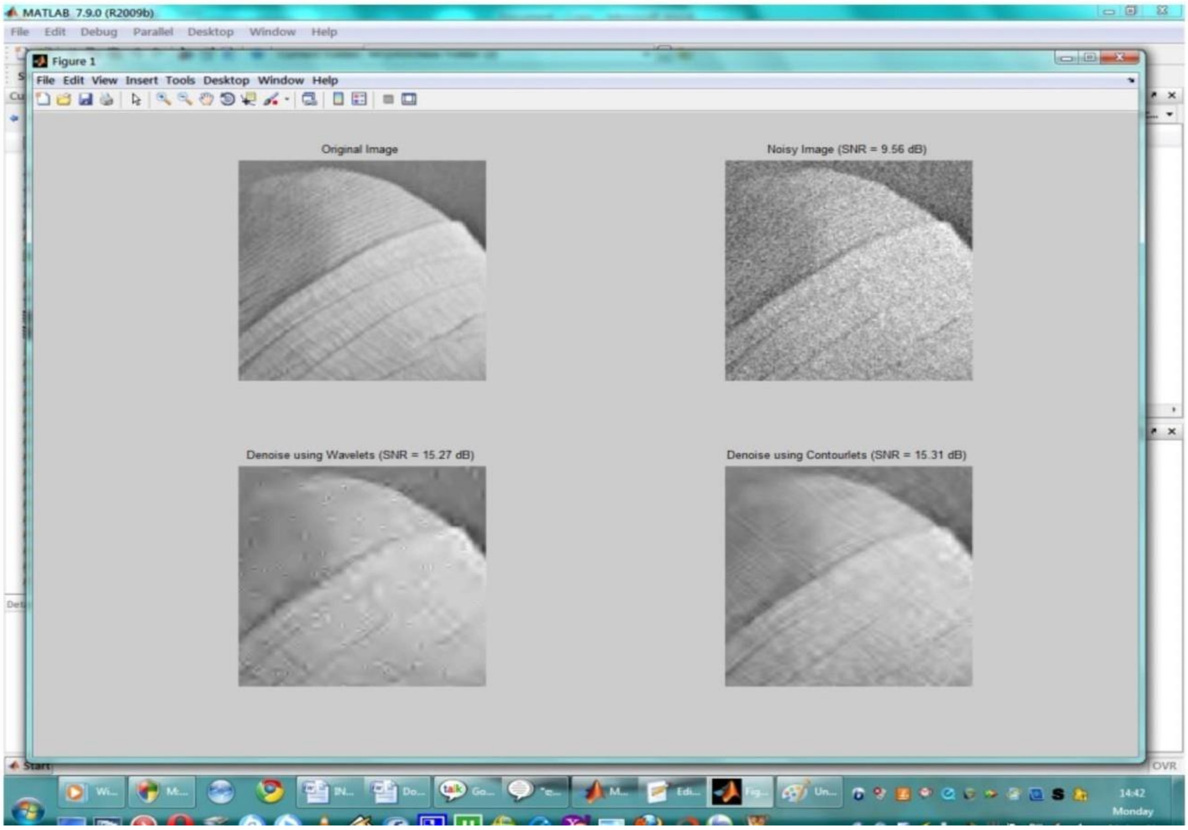
RECONSTRUCTION OF IMAGE USING CONTOURLET



DISPLAYING THE RECONSTRUCTED IMAGE



DENOISING DEMO USING CONTOURLET TRANSFORM



Thus from these results we can conclude that using Contourlet transform we can reconstruct the image efficiently without any errors as Contourlet transform is efficient incapturing the interiors of an image. Wavelet transform: Signal to noise ratio = 15.27 dB Contourlet transform: Signal to noise ratio = 15.31dB

Thus it is clear that Contourlet transform is very much efficient than wavelet transform indenoising a noisy image

Advantages

- It is used for multiresolution.
- It is used to reduce the redundancy.
- Discrete domain implementation

.Multidirectional

Conclusion

Thus by using the transform that we developed here i.e., Contourlet transform we are able to get the accurate image representation as well as denoising of image.

- Offer sparse representation for piecewise smooth images
- Provide multi-scale and multi-direction decomposition
- Small redundance

Future Scope

As we concluded that Contourlet transform is an efficient transformation technique used to represent images in frequency domain, we can use this transformation technique for various applications. But, still for some applications we are not getting the good efficiency. In the future we need to modify this a bit. By using this Contourlet transform efficiently in the future we can be able to solve several real world challenges in Image processing. Besides this effective representation, noise reducing Contourlet transform is useful for several purposes in the future. In the current day scenario also we are applying contourlet for the various purposes. But, still we are hoping for the best results out of it. Hence by using this contourlet transform for all image denoising applications we are able to solve many real world challenges very easily.

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