Contourlet Transforms for Feature Detection

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Abstract

This project will involve the exploration of a directional extension of multidimensional wavelet transforms, called "contourlets", to perform pattern recognition. First, the general concept of a directional extension vs. a regular multidimensional wavelet transform will be discussed and explain the reasoning behind the directional extension. Then, a comparison will be done using sample images between the contourlet transform and other edge detection methods for feature detection.

Introduction

Traditionally, feature detection/extraction was done with a variety of methods, such as Laplacian operators, gradient operators, the Laplacian of Gaussians, difference of Gaussians, Canny detectors, or anisotropic diffusion. However, wavelet transforms have come into light as a means of feature detection. [1]

Typically, feature detection/extraction is a preliminary step in machine learning and machine vision applications. However, there is no perfect edge detector or feature extraction algorithm; one edge detector may work very well in one application, while the exact same algorithm may fail in other applications. Therefore, it is useful to have as many types of algorithms available for evaluation.

This paper aims to explore an edge detection algorithm using contourlet transforms. We will attempt to give a brief overview of the contourlet transform, use it for edge detection, and compare it against other edge detection algorithms.

Background

Wavelets are classified as a linear transform that is capable of displaying the transformed output at multiple resolutions depending on the point of time/space and at the desired frequency. In contrast to the short-time Fourier transform (STFT), the resolution changes depending on the frequency that is to be examined and at what time or spatial area is to be examined. [2]

In the 1-D case, wavelets are used for signal processing by the virtue that wavelets can store more frequency information with less coefficients and reconstruction is only limited by the coefficients that are available. Wavelets can be naively extended to the 2-D case by means of separable functions, but there is limited directional information stored in a regular 2-D wavelet transform. Because of the seperability limitations, only a horizontal, vertical, and 45 degree component can be easily determined. Incidentally, edges can be seen easily, but directional information about the edge is not known. Because of this, it takes more coefficients to do a proper reconstruction of the edges. [3]

Typically, a separable 2-D wavelet transform provides:

- multiresolution, which is the ability to visualize the transform with varying resolution from coarse to fine
- localization, which is the ability of the basis elements to be localized in both the spacial and frequency domains
- critical sampling, which is the ability for the basis elements to have little redundancy.

However, it is not capable of providing:

- directionality, which is having basis elements defined in a variety of directions

- anisotropy, which is having basis elements defined in various aspect ratios and shapes. [4]

There are many directional extensions of the 2-D wavelet transform that could be potentially examined that also possess directionality and anisotropy. The contourlet transform is a discrete extension of the curvelet transform that aims to capture curves instead of points, and provides for directionality and anisotropy. Figure 1 shows the general concept of capturing curves. [5]

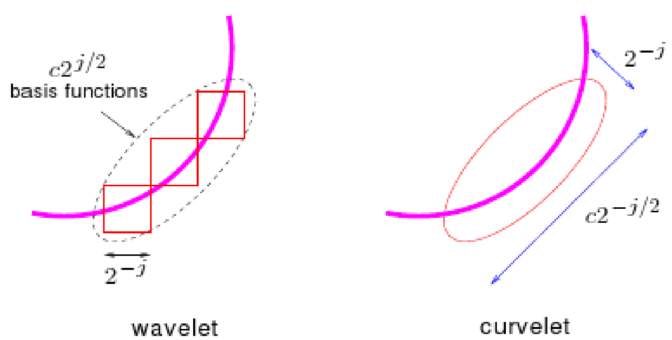

Figure 1: Conceptual visualization of curvelets/contourlets.

Contourlets are implemented by using a filter bank that decouples the multiscale and the directional decompositions. In Figure 2, Do and Vetterli show a conceptual filter bank setup that shows this decoupling. We can see that a multiscale decomposition is done by a Laplacian pyramid, then a directional decomposition is done using a directional filter bank. This transform is suitable for applications involving edge detection with a high curve content. [4]

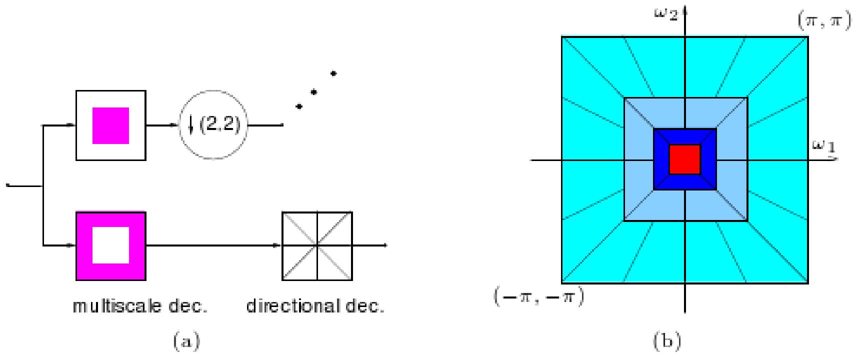

Figure 2: Filter bank for contourlet transform.

Using Contourlets for Edge Detection

Our approach involves taking the contourlet transform of test grayscale images. Code for the contourlet transform is available through the author's web site. [6] The code for the contourlet transform is flexible enough to also do the regular 2-D separable wavelet transform. The edge detection algorithm is as follows:

1. Take the contourlet transform of the image.

2. Choose a scale factor to use, and truncate all other coefficients.

3. Invert the transform.

4. Threshold using the mean of the pixel values of the image.

In addition, there is built in code in MATLAB's Image Processing Toolbox for doing edge detection using the Prewitt gradient operator, the Sobol gradient operator, and Canny's method. These are also run on the test grayscale image for comparison purposes. A MATLAB script is used to automate this process.

Results

The results shown here are not objective results. It is more practical to evaluate the objective performance of a feature extraction algorithm by how the features extracted contribute to a particular application. This type of analysis is beyond the scope of this paper and the reader is referred to papers on machine learning and machine vision.

Figure 3 shows the Lena image. Subjectively, the contourlet detector captures edges here rather well, and does better than Canny's algorithm or with regular wavelets. We use scale factor 1.

Figure 4 shows the Elaine image. Subjectively, the contourlet detector does worse than Canny's method because it has trouble with some of the edges in the background. Again, we use scale factor 1.

Conclusion

In this paper, we have shown that the contourlet transform can be used for edge detection. However, it is not perfect and it is not expected to be perfect. We only performed a subjective analysis because an objective analysis should be done based on how the extracted features are used, such as in a computer-aided detection algorithm or in a machine vision algorithm. Further work is possible to potentially exploit multiple scales for edge detection, reduce the noise that is generated in the edge map, and extend the algorithm to color images.

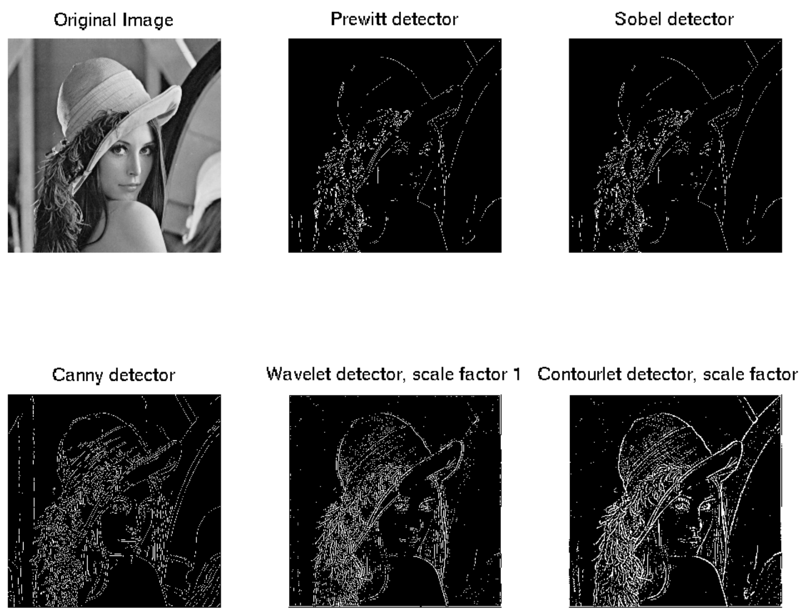

Figure 3: Lena image.

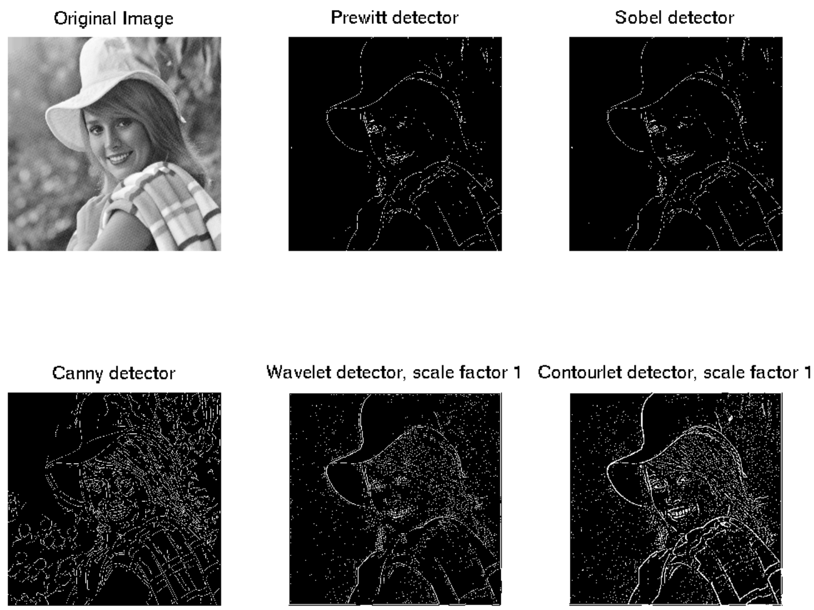

Figure 4: Elaine image.

References

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