Edge Detection by Wavelet Scale Correlation

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Abstract: - The spatial and scale space domain techniques are used independently to detect edges of the noisy images. When noise density surpasses a limit, classical operators are unable to detect the edges. The frequency domain filtering for edge detection in a noisy scenario is inadequate due to Fourier's global behavior. Wavelet analysis for noisy images also reveals dominance of noisy pixels over the edges. Even multiresolution analysis falls short to distinguish noise and edge points in the synthesized image for depleted signal to noise ratio. In this paper noisy images have been decomposed up to fourth level through multilevel wavelet decomposition. The wavelet details coefficients are thresholded by four times the mean value of the image matrix. The lower dimensional wavelet detail's coefficient matrices are interpolated up to the original size of the image. The noisy pixels are partially eliminated at each scale. However in the process, few edge points are also deteriorated. Independently multiplying each detail matrix by its three higher scale image matrices respectively significantly reduces the noise and enhances the directional edges. The reconstruction results in enhanced horizontal, vertical and diagonal details. The three images are synthesized to obtain the augmented edge map of the image.

Key-Words: - Edge detection, Multiscale, Multiresolution, Wavelet, Scale correlation, image denoising.

1. Introduction

The Images are two-dimensional arrays of intensity values with locally varying statistics that result from different combination of abrupt features like edges and contrasting homogeneous regions. Edges[1] are among objects, regions, between objects and backgrounds and are presented by object's geometric edge, shape, object's surface grain and so on. Edge detecting an image significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. If the edges in an image can be identified accurately, all the objects can be located and basic properties such as area, perimeter and shape can be measured which leads to accurate identification and recognition. Edges can be classified [2] into four different profiles: step, ramp, pulse and stair. Edges in images are local singularities. Edge Detection is an essential process in image analysis and many techniques have been proposed. On ground of different needs, different edges should be extracted. These factors make edge detection difficult. Edges can be determined from the image by processing directly in the spatial domain, or by transforming to a different domain.

The classical edge detectors are not well adaptive to handle noisy images. Edges propagate to a certain coarser scales and noisy pixels are un-correlated with the scales, which is being exploited to extract the edge map of a noisy image.

2. Approach and Method

The purpose of this paper is to develop an algorithm to detect connected and disconnected boundaries in an image such that it incorporates an efficient technique for noise elimination vis-à-vis exiting conventional operators [3]. The proposed method favours edges that exist at multiple scales and suppress edges that exist at fine scales. Wavelet transform has the advantage of locally analysing in spatial and frequency domain. Multiscale edge detection methods [4-6] have other advantages. In this paper scale multiplication based edge detection scheme is worked out by multiplying four adjacent subbands as a product function. Execution time is little longer for complex images due to convolution operation between the mirror filters and the whole image running at the background. In this paper an effort has been made to determine edges at the local maxima in the product function after thresholding. Unlike many multiscale edge detectors, where the edge maps were found at several scales and then synthesized together. Scale multiplication achieves better results than either of the two scales, especially on the localization performance. An efficient integrated edge map will be evaluated. Significant improvement is attained through this technique vis-à-vis existing methods. Experiments on benchmark images have been made using classical spatial domain filters, frequency domain filters and wavelet filters with wavelet scale correlation edge detection algorithms.

3. Edge Detection Using Wavelet Transform

Edge detectors are actually discritized wavelet functions and convolution with these operators gives the wavelet transform of the image at certain scale. Approximation of continuous wavelet model with dyadic discretization results in classical edge detectors. The scale of the wavelet can be adjusted to detect edges of different level of scale. Coarser scale results in undetected edges and fine scale results in noisy and discontinuous edges. For coarser scale the coefficients of wavelet transform increase for step edges and decreases for dirac and fractal edges. The scale of edge detector is adjustable to control the edge significance in contrast to classical edge operators. A larger scale wavelet can be used at positions where the wavelet transform decreases rapidly across scales to remove the effect of noise while using a smaller scale wavelet at positions where the wavelet transform decrease slowly across scale to preserve the precise position of the edge. Wavelet filters of large scales are more effective for removing noise, but at the same time increases the uncertainty of the location of edges. Wavelet filters of small scales preserves the exact location of edges but cannot distinguish between noise and real edges.

Edge detection in noisy scenario can be treated as an optimal linear filter design problem [7 8]. Most of the image processing algorithms use Quadrature Mirror Filter pair (QMF) to perform multiresolution analysis[9-10]. Such analysis of images with QMF has been used to exploit both detailing and smoothing capabilities of wavelets to get the detail images. The scaling function and the wavelets in one dimensional space can be given by the following general formula:

$$\varphi_{a,b}(x) = (a)^{-1/2}\varphi\left(\frac{x-b}{a}\right)\ldots a \succ 0, b \in R \quad (1)$$

$$\psi_{a,b}(x) = (a)^{-1/2}\psi\left(\frac{x-b}{a}\right)\ldots a \succ 0, b \in R \quad (2)$$

Where, $\varphi_{a,b}(x)$ is the family of scaling function at scale *a* and translated by *b*, $\psi_{a,b}(x)$ is the family of wavelets at scale *a* and translated by *b*, *a* is the scaling factor, b is the translation desired, and φ and ψ are $\varphi_{0,0}$ and $\psi_{0,0}$ respectively.

In two dimensional spaces one scaling function and three wavelets are needed. The scaling function is defined as

$$\varphi(x,y) = \varphi(x)\varphi(y) \quad (3)$$

and the three wavelet functions as

$$\psi^1(x,y) = \varphi(x)\psi(y) \quad (4)$$

$$\psi^2(x,y) = \psi(x)\varphi(y) \quad (5)$$

$$\psi^3(x,y) = \psi(x)\psi(y) \quad (6)$$

The scale is not varied to avoid lower resolution on account of increasing scale. What has been done is to perform one scale decomposition and obtain the edges at that level by extracting the detailing images and then proceed on to further analysis with the lowpass residue. With this methodology better edges could be obtained using Orthogonal and biorthogonal wavelets. The horizontal ψ^1, vertical ψ^2 and diagonal ψ^3 components are nothing but the gradient of the image along the x, y and diagonal directions. Following this the magnitude of the image is taken at every level of decomposition, which on thresholding gives the edges at that level of decomposition. Thresholding has been done following common criteria for both wavelet and conventional operators so as to facilitate criteria for comparison. With every subsequent level of decomposition the high frequency details go away. This approach has shown promising results in comparison to conventional operators as it offers a lot of flexibility in the form of multilevel decomposition. Depending on the requirement of details desired the level of decomposition may be carried out. With this approach even edges of noisy images have been obtained successfully and the same has been shown with experiments.

4. Proposed Methodology

The edges of the input image are extracted at different scales through multilevel decomposition of the image as following: -

1. A pair of QMF is applied on the gray-level image.

2. High Frequency details H at level-1 are extracted and used to get the magnitude image of horizontal and vertical details.
3. On the magnitude image so obtained thresholding is performed to obtain the edge detected image at level-1.
4. Lowpass residue of level-1 is taken for analysis to get 2nd level decomposition.
5. Steps 1, 2, and 3 are performed on level-2 magnitude image to obtain edge detected image at level-2.
6. Lowpass residues is carried over from previous level to iterate up to level-4

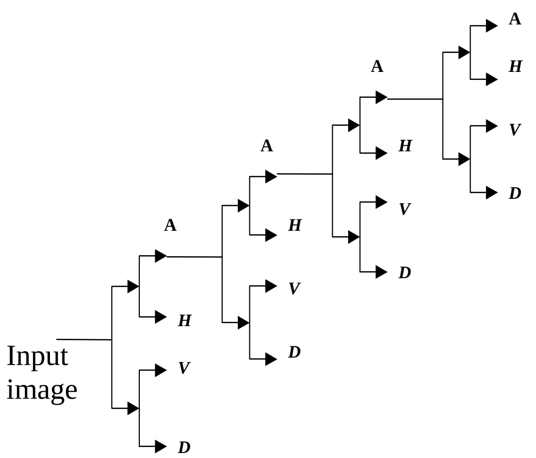

*Figure 1. Wavelet decomposition at level 4. **A** denotes approximations, **H** horizontal details, **V** vertical details and **D** diagonal details.*

Above algorithm is an iterative process. Image being passed on to the following stage every time gets smoothed as the high frequency details are extracted at every level. This scheme is especially very useful in getting edges of a noisy image. In this paper the results so attained are through level four decomposition of the image by wavelets. The values of the wavelet coefficients are thresholded. The threshold is taken as four times the mean value of the matrix. Each of the detail component after synthesizing to original size of the image is multiplied by its all four dimensional respective component such that

$$D^H = \psi_v^H * \psi_{v+1}^H * \psi_{v+2}^H * \psi_{v+3}^H \quad (7)$$

$$D^V = \psi_v^V * \psi_{v+1}^V * \psi_{v+2}^V * \psi_{v+3}^V \quad (8)$$

$$D^D = \psi_v^D * \psi_{v+1}^D * \psi_{v+2}^D * \psi_{v+3}^D \quad (9)$$

$$E = D^H + D^V + D^D \quad (10)$$

where $v \in L^2$, D represents respective detail coefficients superscript H, V and D represents horizontal vertical and diagonal details while E represents the combined edge map. The edge structure remains in contact in the fine scale where as noise is eliminated as per the scale variation. The directional edges are taken at various resolutions and the image matrices so attained are interpolated to the original dimension of the image to execute matrix multiplication. In the process the directional details are enhanced and isolated noisy pixels are eliminated due to its non existence in lower dimensional space.

Experiments are conducted using Haar(db1) to Daubechies (db8) and Bior(3.7) which revealed comparable results with classical operators for high signal to noise ratio (SNR) images. Results for Uniform noise in the image are trivial due to wavelets in built approximating and detailing characteristics. Figure 2 demonstrates Gaussian noise with varying mean and variance induced to Lena image of figure-3 for experimental purpose. Adequate results were achieved for low SNR where spatial as well as frequency domain operators fall short to give any significant intelligence about the edge map of the noisy image.

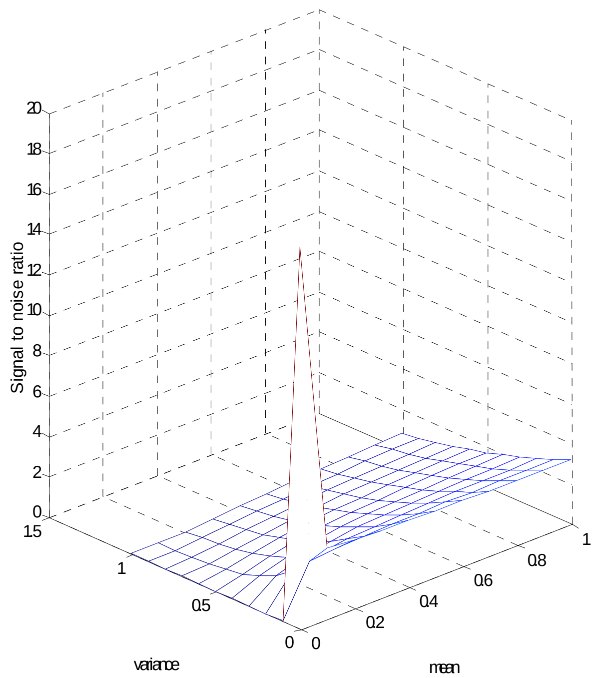

Figure 2. SNR when Gaussian noise induced in the Lena image for varying mean and variance

The proposed scheme although some of the edge pixels were found missing, outperformed and gave adequate results. The edge map by wavelet scale correlation applied to Lena image figure 3 with Gaussian noise of zero mean and one variance figure 4(a) and 0.5 noise density Salt & Pepper noise figure 4(c) are shown in figure 4(b) and 4(d) respectively.

Figure 3. Lena image used to illustrate experimental results.

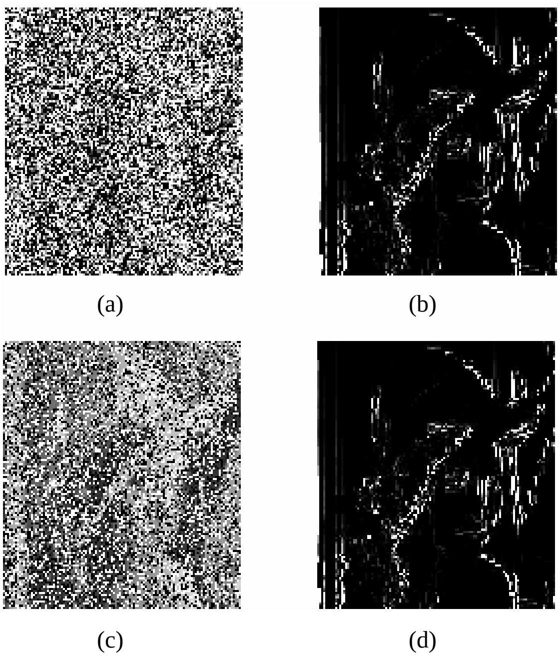

Figure 4. Edges extracted by wavelet scale correlation upto 4^{th} level scale correlation from noisy Lena Image. (a) Gaussian noise induced with μ=0& σ=1. (b) Edges detected from (a). (c) Salt & Pepper noise with 0.5 noise density. (d) Edges detected from (c).

5. CONCLUSION

In this paper an algorithm for the multilevel wavelet edge detection through wavelet scale correlation of the adjacent spaces respectively, has been developed. The comparison of wavelets and traditional edge detection techniques on images in noisy environment is performed. A database of edge detected images in noisy environment is subjected to psychovisual comparison. Edge detection through wavelets found to be better than spatial and frequency domain edge detection operators. The proposed method favors edges that exist at multiple scales and suppress edges that only exist at finer scales. Lesser the length of wavelet coefficients, better is the edge detection results; db1 gave the best results with in the wavelets for edge detection for the test images while being computationally comparable with classical operators. The noise is highly un-correlated amongst the subbands. Scale correlation of adjacent bands depletes the noise pixels and reveals the edge structure of the image. Proposed scheme of edge detection has outperformed the classical edge detectors for depleted SNR images.

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