Edge Detection In Images Using Haar Wavelets, Sobel, Gabor And Laplacian Filters

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Abstract: Edge detection is a fundamental technique that precedes and enables feature understanding in image analysis. It is a very important technique in computer vision. Wavelets, Sobel operators, and Gabor filters have been used extensively in the literature for edge detection in images. Each of these filters has their strengths and limitations. This paper suggests edge detection in images using a combination of Gabor filters, Laplacian filter and Sobel operators which produce better results than using the individual filters.

KEYWORDS: Edge-detection, Gabor, Laplacian, Sobel, wavelets, Haar, thresholding, image processing.

1 INTRODUCTION

An edge is a location in an image where the level of luminescence or gray level changes abruptly [1, 2]. It marks the boundary of discontinuity or strong contrast in luminescence in an image. An image without an edge would not make sense to the eyes because edges make it possible to understand an image. Edge detection is a fundamental step in image analysis and machine vision systems analyze an image by identifying edges in an image or visual data. Edge detection is a pattern recognition problem to an extent and is challenging; the irony in life is that what is perceived easily in human vision is quite complex in computer and machine vision. Edge detection is a very important technique in computer and machine vision [2-5] and is useful but not limited to the following applications: biometric recognition, automatic character recognition, document processing, remote sensing, medical imaging, surveillance, automotive sensing, human-computer interaction and visual inspection. Edge detection precedes image segmentation and feature extraction stages in image analysis and also acts as a dimensionality reduction technique in feature extraction. In this sense, only relevant features in an image sufficient to identify the image are extracted while redundant features are discarded. Several classical edge detectors have been used for detecting edges in images like the Sobel and Canny operators [6]. These operators work based on thresholding the pixels within a specified window. An operator may take the average value of pixels within a window as the threshold and may be likened to an averaging filter. The threshold then depends on the presence, absence and the value of the pixels within that window. These classical edge detectors have limitations in detecting edges in noisy and faint images. Meaningful and spurious edges are likely to be detected in a noisy image while edges could be omitted in a faint image, hence, classical operators cannot adequately analyze noisy images. Most signals encountered in life, in real-time (audio, video, image, motion, pressure) have some degree of noise; hence, a reliable edge detection technique should be sensitive to edges and insensitive to noise. Wavelets have been found quite useful in image edge detection [3, 7-9].

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A wavelet is an orthogonal wave for which the resultant integral is zero [10, 11]. The wavelet transform ensures both frequency and time information in the analyzed signal. The vertical and horizontal details of the wavelet decomposition are useful features for extracting edges in images through a thresholding operation is required to filter out noise in the combined image. Laplacian filters may be directly used to detect edges in images since it is a high pass or differential spatial filter. Gabor filters and wavelets are used in edge detection [12] due to the advantage of their efficiency in multi-resolution analysis and optimization of time and frequency resolutions. Unlike wavelets that have to reach a compromise between frequency and time resolution, Gabor filters efficiently optimize both frequency and time resolutions. This means that it is possible to have good frequency and time resolutions at the same scale using Gabor filters. This property gives them an added advantage over wavelets in edge detection. Sobel operators, Wavelets, Laplacian filters and Gabor filters all have their strengths and drawbacks as edge detectors. Edges derived with the Gabor filter are over-detailed but blurred while edges detected with the Laplacian filter are faint. This paper suggests approaches for edge detection using a combination of filters: Gabor and Laplacian, Sobel and Gabor, Gabor, Sobel, and Laplacian with better results than using the filters individually.

2 EDGE DETECTORS

2.1 Haar wavelet Edge Detector

A wavelet transforms using a wavelet function, $\psi(t)$, is defined as [10, 11]:

$$\psi(\tau, s) = \frac{1}{\sqrt{s}} \int x(t)\, \psi'\left(\frac{t-\tau}{s}\right) dt \quad (1)$$

where ψ' is the mother wavelet, τ and s are the translation and scale parameters respectively. Equation (1) describes a continuous wavelet transform. The scale parameter is related to the frequency though inversely. In discrete wavelet transform (DWT) the varying of the time resolution and frequency resolution (scaling) properties are achieved with the use of filters (high-pass and low-pass) and sub-sampling respectively. Scaling is achieved by successively passing the input signal through half-band cutoff low-pass and high-pass filters [10, 11, 13] and sub-sampling the outputs of both filters. In 2D-DWT, the transform is first applied to the columns of the image which consistently halves the sizes of all columns in the image and then applied to the rows in like manner. The resultant image would be reduced or sub-sampled by 4. Haar wavelets were used in this paper. Haar wavelets decompose an image of size N×M into four sub-images of sizes N/2×M/2, where N and M are even. The decomposed images are the approximation image (A) and vertical (V), horizontal (H) and diagonal (D) differences' images. The differences' images show how the neighboring pixels differ in the vertical, horizontal and diagonal directions. A two Haar level decomposition of an image gives rise to approximation (A1 and A2) as well as details (D1, D2, V1, H1, V2, and H2) images. Edges can be found in regions of high contrast, therefore, more attention was given to the coefficients derived from high-pass filtering of the image. Hence, the Haar decomposed images useful for edge detection are the differences' images.

2.2 Edge Detection using Gabor filters

A Gabor filter is a linear filter whose impulse response is a product of a harmonic and Gaussian function [14, 15]. It may be one or two dimensional. A 2D Gabor function may be expressed as [14, 16]:

$$g(x,y,\lambda,\emptyset,\psi,\sigma,\gamma) = e^{\left(\frac{-x'^2+\gamma^2 y'^2}{2\sigma^2}\right)} \cos\left(\frac{2\pi x'}{\lambda}+\psi\right) \quad (2)$$

$$g(x,y,\lambda,\emptyset,\psi,\sigma,\gamma) = e^{\left(\frac{-x'^2+\gamma^2 y'^2}{2\sigma^2}\right)} \sin\left(\frac{2\pi x'}{\lambda}+\psi\right) \quad (3)$$

where $x' = x\cos\phi + y\sin\phi$ (4)

where $y' = y\cos\phi - x\sin\phi$ (5)

x and y are the coordinates in the image
λ is the wavelength of the harmonic wave
ϕ is the orientation of the Gabor function. The orientation, ϕ, is in the range [0, 2π].
ψ is the phase shift of the Gabor function
γ is the spatial aspect ratio, while σ is the standard deviation of the Gaussian function which determines the spread of the bell-shaped Gaussian function A bank of Gabor filters with four wavelengths, λ = 2, 4, 6 and 8, and 24 orientations ranging from 0 to 23π/12 was convolved with an image in this paper. It is the summation of all the 96 filter responses that produce a complete edge image.

2.3 Effect of Gabor Orientation on Edge Image Quality

The number of orientations does have an effect on edge image quality. Six edge images of Lena image extracted using Gabor filters at 2, 3, 6, 12, 24 and 60 number of orientations each at wavelengths 2, 4, 6 and 8 are shown in

Fig. *1* (a), (b), (c), (d), (e) and (f) respectively in this paper. The angles of the orientations in each filtering increase by an equal step quantity. That is, in (a) the two orientations are ϕ = 0 and ϕ = π/2. In

Fig. *1* (b) the three orientations are ϕ = 0, ϕ = π/3 and ϕ = 2π/3. Edge images (e) and (f) are extracted within the range [0 - 2π] while the rest are extracted from the range [0 – π]. At least 12 orientations and not more than 24 orientations are required to sufficiently detect edges in images.

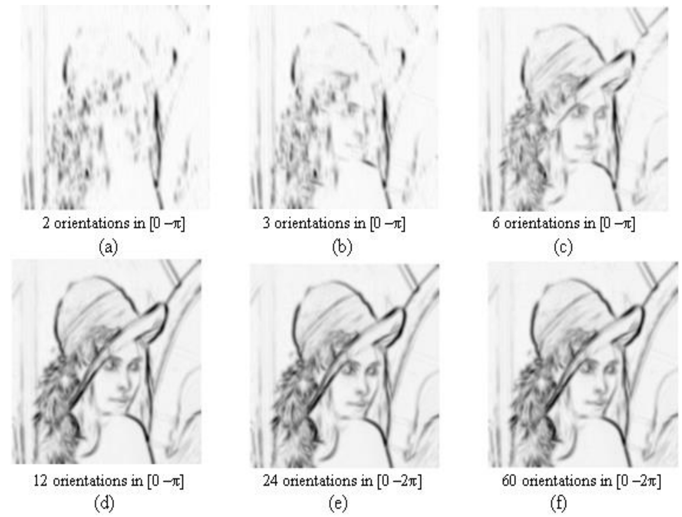

Fig. 1. *Six edge images of Lena image extracted using Gabor filters using the following number of orientations (a) 2 within [0 – π], (b) 3 within [0 – π], (c) 6 within [0 – π], (d) 12 within [0 – π], (e) 24 within [0 – 2π] and (f) 60 within [0 – 2π]*

3. PROPOSED EDGE DETECTION APPROACHES

Edge detection is typically carried out with Gabor, Sobel or Laplacian filter. However, in this paper, we carry out edge detection with a combination of the following filters: a) Laplacian and Gabor, b) Sobel and Gabor c) Gabor, Sobel, and Laplacian

3.1 Edge detection using Laplacian-Gabor filters

Given an original image, the first edge image is obtained by convolving the original image with the 96 Gabor filters corresponding to 24 orientations, θ, within [0 – 2π] and 4 wavelengths, λ. Let $\{I_{(j,k)} \mid j = 0,1,\dots n-1; k = 0,1,\dots m-1\}$ or $i[n,m]$ be the original image with size M×N. Let the impulse response of a Gabor filter, $G_{x,y}$, be $g[n,m]$. The size of the Gabor filter is resized to m,n by padding with zeros. A 2D convolution of an image with a Gabor filter for one wavelength and specific orientation may be represented as:

$$C = \sum_{j=0}^{M-1}\sum_{k=0}^{N-1} i[j]g[m-j].i[k]g[n-k] \quad (1)$$

In Equation (6) a Gabor filter with the response, $g[m,n]$, is convolved with an image, $I_{(j,k)}$, at a particular filter wavelength, λ, and orientation, ϕ. Edge detection using **r** Gabor filters involves convolving an image with a bank of filters with wavelengths, λ_1, λ_2, … λ_r, and orientations ϕ_1, ϕ_2, … ϕ_{24}. Let the edge image be $E_{j,k}$. This may be expressed as:

$$E_{j,k} = \sum_{w=0}^{r-1}\sum_{j=0}^{M-1}\sum_{k=0}^{N-1} C(w) + \left(i[j]g[m-j].i[k]g[n-k]\right) \quad (2)$$

where w denotes a wavelength or scale at the particular orientation while **r** is the number of filters in a bank of filters. An intermediary Laplacian image, $L'_{o_{j,k}}$, is obtained by convolving the original image with a Laplacian filter, $l[m,n]$.

$$L'_{o_{j,k}} = l'_o[m,n] = \sum_{j=0}^{M-1}\sum_{k=0}^{N-1} x[j]l[m-j].y[k]l[n-k] \quad (3)$$

The final edge image is obtained by taking the difference between the Gabor edge image and Laplacian image. This image is the Laplacian-Gabor edge image, $\mathbf{LG_{j,k}}$.

$$LG_{j,k} = E_{j,k} - L'_{o_{j,k}} \quad (4)$$

3.2 Edge detection using Sobel-Gabor Filters

A Gabor edge image, $\{E_{(j,k)} \mid j = 0,1,\ldots n; k = 0,1,\ldots m\}$, or, $e[n,m]$, is first obtained from the original image using the equation defined in (7). The Sobel image of the Gabor image is obtained by convolving the Gabor edge image with a Sobel filter of response, $s'_o[n,m]$, resulting in an image, $\mathbf{S_{x,y}}$ as follows:

$$S_{x,y} = s[n,m] = e[n,m] * s'_o[n,m] \quad (5)$$

Finally, the Sobel-Gabor edge image, $\mathbf{SG_{x,y}}$. is obtained as follows:

$$SG_{x,y} = E_{x,y} - S_{x,y} \quad (6)$$

3.3 Edge detection using Laplacian of Sobel-Gabor Filters

In this case, the original image is convolved successively with three filters, Gabor, Sobel, and Laplacian. The Laplacian-Sobel-Gabor image, $LSG_{x,y}$ is obtained in the following order: The original image is convolved with a bank of Gabor filters resulting in $E_{x,y}$:

$$E_{x,y} = e[n,m] = i[n,m] * g[n,m] \quad (7)$$

Sobel edge image of Gabor edge image, $SG_{x,y}$, is obtained as follows:

$$S_{x,y} = s[n,m] = e[n,m] * s'_o[n,m] \quad (8)$$

where $s'_o[n,m]$ is the Sobel filter response

$$SG_{x,y} = E_{x,y} - S_{x,y} \quad (9)$$

The Laplacian filtering of image, $SG_{x,y}$, gives the intermediate image, $LSG'_{o_{x,y}}$,

$$LSG'_{o_{x,y}} = SG_{x,y} * l'_o[n,m] \quad (10)$$

where $l'_o[n,m]$ is the Laplacian filter response Finally, the Laplacian-Sobel-Gabor image, $LSG_{x,y}$ is determined as:

$$LSG_{x,y} = SG_{x,y} - LSG'_{o_{x,y}} \quad (11)$$

4. EXPERIMENTS, RESULTS, AND DISCUSSION

Experiments were carried out using the popular Lena image. Two-level Haar wavelet decomposition was carried out on the original Lena image and the horizontal and vertical images were combined after a thresholding operation was carried out to filter out a noise. The Gabor filter parameters used within 24 filter orientations ranging from [0 – 2π] in steps of π/12 and at wavelengths, λ = 2, 4, 6 and 8, were phase shift, ψ = [0 - π], spatial aspect ratio, γ = 0.5, standard deviation = 1. Linear spatial filters, s'_o and l'_o, of 3×3 window sizes were created for the Sobel and Laplacian filters, respectively.

$$s'_o = \begin{Bmatrix} 1 & 1.5 & 1 \\ 0 & 0 & 0 \\ -1 & -1.5 & -1 \end{Bmatrix} \; and \; l'_o = \begin{Bmatrix} 0.090 & 0.818 & 0.090 \\ 0.818 & -3.636 & 0.181 \\ 0.090 & 0.818 & 0.090 \end{Bmatrix}$$

The result of edge detection on the original image in **Fig. *2*** (a), using Haar wavelet is shown in **Fig. *2*** (b). Results of convolving the original image with typical filters - Laplacian, Gabor, Sobel are shown in **Fig. *2*** (c), (d) and (e), respectively. Results of convolving the original image with proposed filters - Laplacian of Gabor, Sobel of Gabor and Laplacian of Sobel of Gabor are shown in **Fig. *2*** (f), (g) and (h), respectively. Edges detected using Haar wavelets in **Fig. *2*** (b) are broken and not so pronounced. Edges detected in **Fig. *2*** (c) are faded and can hardly be seen. There are missing edges in the edge image derived using Haar wavelets in **Fig. *2*** (a) while the Laplacian image in **Fig. *2*** (c) is very faint. The Gabor edges in **Fig. *2*** (d) are pronounced but blurred while the Sobel image in **Fig. *2*** (e) is embossed, fine but faint. Edges detected using the proposed Laplacian of Gabor filter in **Fig. *2*** (f) is sharp and better than the Laplacian or Gabor based edges image in **Fig. *2*** (c) and (d). The Sobel of Gabor image in **Fig. *2*** (g) has well defined and embossed edges, sharper than the edge image in **Fig. *2*** (e). Edge image in **Fig. *2*** (h) detected with the Laplacian of Sobel of Gabor is softly embossed, sharp and detailed. The results show that use of these three filters - Laplacian of Gabor filter, Sobel of Gabor filter and Laplacian of Sobel of Gabor performs better in detecting edges in images compared to using these filters singly.

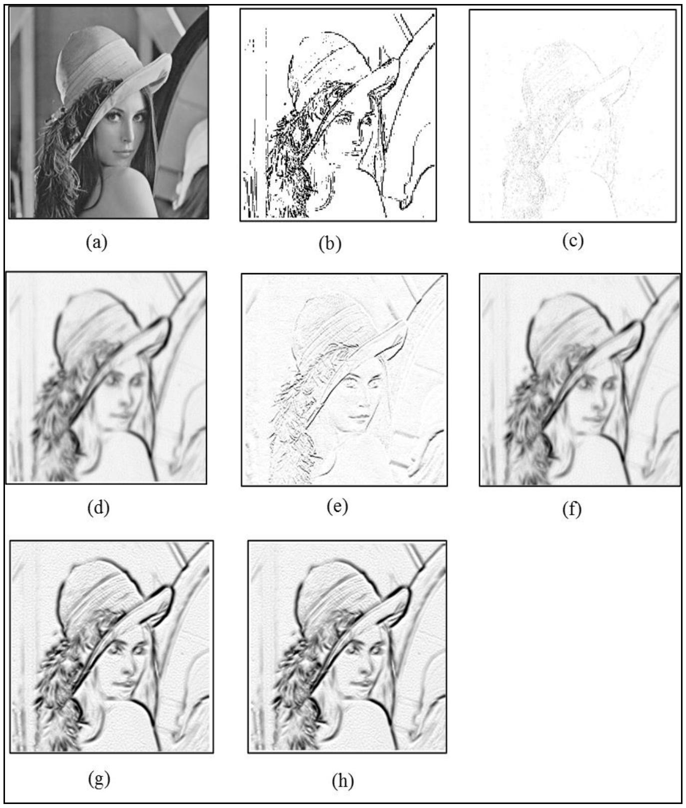

Fig. 2. *Original image (b) Haar (c) Laplacian, (d) Gabor, (e) Sobel (f) Laplacian of Gabor [proposed] (g) Sobel of Gabor and [proposed] (h) Laplacian of Sobel of Gabor [proposed].*

5. CONCLUSION

High pass filters such as Gabor and Laplacian filters are used for edge detection in images but with some limitations such as the resulting blurred and faint edge images respectively. This paper, therefore, suggests edge detection in images using a combination of Gabor filters, Laplacian filter and Sobel operators namely: Laplacian of Gabor, Sobel of Gabor and the Laplacian of Sobel of Gabor filters. These combinations produce better results than using the individual filters and hence may be beneficial for edge-detection in images.

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