Robust Edge Detection Based on Non-Local Contribution of Local Frequency Characteristics

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Abstract

This paper introduces a robust approach to the problem of edge detection in situations characterized by high levels of image degradation and illumination non-uniformity. Popular edge detection methods are dependent solely on local image characteristics to localize edge information. In the proposed algorithm, we demonstrate that superior edge detection performance can be achieved by utilizing non-local image characteristics. This is accomplished by estimating the edge strength of a given pixel based on the local frequency characteristics of every pixel within an image. The proposed method is highly robust to scenarios characterized by illumination non-uniformity and low signal-to-noise ratios. Experimental results show that using the proposed method, edge detection can be qualitatively improved over existing methods on a small set of test images.

1 Introduction

One of the most important tasks in computer vision and pattern recognition is edge detection, where edge characteristics are extracted from a given image. Such structural characteristics are very important in computer vision applications such as scene analysis, motion tracking, character recognition, and robotic vision. There are many issues that make edge detection a particularly challenging problem to solve in real-world situations. First, it is often the case that an image being analyzed is contaminated by noise and other forms of image degradation due to intrinsic and extrinsic factors. Furthermore, illumination and contrast non-uniformity make it difficult to identify edge characteristics in a consistent manner. Finally, it can be difficult to localize edge characteristics due to scale differences in image structures. Therefore, a edge detection method that is robust to the aforementioned issues is desired.

Many algorithms have been proposed for the purpose of edge detection. These can be generally grouped into three main categories:

1. First-order methods (e.g., Roberts, Prewitt, Sobel, Canny [1]),
2. Second-order methods (e.g., Marr-Hildreth [2], Lindeberg [3]), and
3. Wavelet-based methods [4, 5, 6, 7].

While the Canny method remains one of the most widely used edge detection algorithms, recent research into edge detection has focused on multi-scale wavelet models. Wavelet-based methods are less sensitive to image noise as edge characteristics are extracted across multiple scales. Since image noise typically manifests itself at finer scales, edge detection across different wavelet scales allows edge characteristics caused by noise to be removed without pre-filtering. It is important to note that the proposed wavelet-based algorithm can be integrated into a Canny edge detector since a Canny edge detector can utilize any positively-weighted edge strength map as its basis of edge extraction.

One characteristic shared by all popular edge detection methods is that they are dependent solely on local image characteristics to determine edge information. As such, these techniques are limited to the information within a small neighborhood around a particular pixel. In this paper, we propose that superior edge detection performance can be achieved with an alternative approach by utilizing non-local image characteristics from across the entire image. This alternative approach is inspired by the human vision system, which is able to infer structural characteristics in situations characterized by noise and visual degradation based on patterns found in the surrounding environment. The proposed algorithm extends upon the basic local edge detection concepts presented in [7] such that the edge strength of a given

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pixel is estimated based on the local frequency characteristics of every pixel within an image. This technique is robust to scenarios that are characterized by illumination and contrast conditions as well as low signal-to-noise ratios.

This paper is organized as follows. The proposed edge detection algorithm is described in Section 2. Experimental results are presented and discussed in Section 3. Finally, conclusions are drawn in Section 4.

2 Proposed Algorithm

The proposed algorithm is a multi-scale, complex-valued wavelet approach that utilizes the local frequency characteristics of every pixel in the image. It can be broken up into the following steps. First, the local frequency characteristics are computed for each pixel of the image using complex-valued wavelets at multiple scales. The multi-scale local frequency characteristics at each pixel are then combined into a single local frequency characteristic feature based on a model of the human vision system. Finally, the edge strength of each pixel in the image is estimated through a weighted aggregation of the combined local frequency characteristic features of every pixel in the image.

2.1 Extraction and Combination of Local Frequency Characteristics

The first step in the proposed algorithm is to extract the local frequency characteristics of each pixel at multiple scales and orientations, and combine them into a single local frequency characteristic feature at each pixel based on a model of the human vision system. A recent approach to combining local frequency characteristics into a single local frequency characteristic feature that has been shown to be effective is that based on the local phase coherence model [8, 7, 9]. This approach has been shown to effectively model the sensitivity of the human vision system to structural characteristics in visual data [8]. This concept has been further enhanced in the approach proposed by Kovesi [7], where variations in local phase coherence due to orientation is taken into account. As such, the approach used in the proposed algorithm to combine local frequency characteristics of each pixel across multiple scales and orientations is based on the aforementioned approach. The local amplitude and phase characteristics pertaining to each pixel are first extracted using a complex-valued wavelet transform at multiple scales and orientation (e.g., Gabor wavelet transform, Dual-tree complex wavelet transform, etc.). The local phase coherence at each pixel is the computed by combining the local frequency characteristics of each pixel in the following manner:

$$P(\underline{x},\theta) = \frac{\sum_n W(\underline{x},\theta) \lfloor A_n(\underline{x},\theta)\, \Delta\Phi(\underline{x},\theta) - T \rfloor}{\sum_n A_n(\underline{x},\theta) + \varepsilon} \quad (1)$$

$$\Delta\Phi_n(\underline{x},\theta) = \cos\left(\phi_n(\underline{x},\theta) - \bar{\phi}(\underline{x},\theta)\right) - \left|\sin\left(\phi_n(\underline{x},\theta) - \bar{\phi}(\underline{x},\theta)\right)\right| \quad (2)$$

where W represents the frequency spread weighting factor, A_n and ϕ_n represents the amplitude and phase at wavelet scale n respectively, $\bar{\phi}$ represents the weighted mean phase, T represents the noise threshold and ε is a small constant used to avoid division by zero.

To take the variations in local phase coherence due to orientation into account, the maximum moment of phase coherence at each pixel is then determined by combining the local phase coherences across multiple orientations in the following manner:

$$\kappa(\underline{x}) = \frac{1}{2}\left(\sum_\theta \left[(P(\underline{x},\theta)\sin(\theta))^2 + (P(\underline{x},\theta)\cos(\theta))^2 \right] + \sqrt{ 4\left(\sum_\theta (P(\underline{x},\theta)\sin(\theta))\,(P(\underline{x},\theta)\cos(\theta)) \right)^2 + \left(\sum_\theta \left[(P(\underline{x},\theta)\cos(\theta))^2 - (P(\underline{x},\theta)\sin(\theta))^2 \right] \right)^2 } \right) \quad (3)$$

where $P(\underline{x},\theta)$ is the local phase coherence at orientation θ. The maximum moment of phase coherence at each pixel provides information about its structural characteristics so it can be used to estimate the edge strength of pixels within the image.

2.2 Estimation of Edge Strength

The next step in the proposed algorithm is to estimate the edge strength of each pixel based on the local frequency characteristics of all pixels within the image. As such, it is necessary to devise a method for aggregating the maximum moments of phase coherence of all pixels in a weighted manner such that the estimated edge strength reflects the underlying characteristics of each pixel in the image. The weighted aggregation approach taken in the proposed algorithm is based on the concept of non-local means [11, 10], where the contribution of information at one point to the estimation of information at another point is weighted based on the similarity of local neighborhoods. In the proposed algorithm, the contribution of local frequency characteristics at one pixel to the estimation of the edge strength at another pixel is weighted based on the similarity of maximum moments of local phase coherence within local neighborhoods. Based on this concept, the estimated edge strength $\hat{e}$ at a pixel $\underline{p}$ can be calculated as the weighted aggregation of maximum moments of local phase coherence in the following manner:

$$\hat{e}(\underline{p}) = \sum_{\underline{q} \in I} w(\underline{p}, \underline{q}) \kappa(\underline{q}) \quad (4)$$

where $w(\underline{p}, \underline{q})$ is a weighting function that evaluates the similarity of maximum moments of local phase coherence between the local neighborhoods of two pixels at $\underline{p}$ and $\underline{q}$ respectively. The weighting function can be expressed in the following manner:

$$w(\underline{p}, \underline{q}) = \frac{1}{Z(\underline{p})} e^{-\frac{\left(\frac{1}{2\pi\sigma} e^{-\left(\frac{(\varsigma)^2}{2\sigma^2}\right)} \|\kappa(\varsigma_p) - \kappa(\varsigma_q)\|_2^2 \right)}{\lambda^2}} \quad (5)$$

where ς_p and ς_q represents the local neighborhood around $\underline{p}$ and $\underline{q}$ respectively, ς represents a region with the same neighborhood size as ς_p and ς_q, $Z(\underline{p})$ is a normalization term defined as $Z(\underline{p}) = \sum_{\underline{q}} w(\underline{p}, \underline{q})$, and λ is the relaxation coefficient that can be adjusted based on the degree of approximation desired.

3 Experimental Results

To test the effectiveness of the proposed algorithm for improved edge detection, a test set of five carefully chosen images was contaminated with White Gaussian noise. The resulting test set images exhibit illumination non-uniformity and low signal-to-noise ratios. An edge strength map was computed for each image using the proposed method. For purposes of comparison, edge strength maps were generated using the Sobel operator and multi-scale edge detection using the Roberts operator. For the Sobel operator, the noisy image was pre-filtered using a Gaussian smoothing kernel to reduce the effect of noise on the edge detection process. This smoothing process is the same as that performed in the Canny edge detector, which utilizes such first-order derivative operators for finding the gradient of an image. The resulting edge strength maps for each of the test images are shown in Figure 1, Figure 2, Figure 3, Figure 4, and Figure 5. It can be seen that the proposed method is able to extract highly localized edges at the correct scale. Furthermore, it can be observed in TEST3 that the edge strength for the proposed method is largely unaffected by illumination variations. More importantly, it can be observed that the proposed algorithm produces edge strength maps that are noticeably more structurally consistent than the other methods. This can be attributed to the fact that the proposed method utilizes structural characteristics from the entire image to compensate for structural degradation caused by the presence of significant amounts of noise. These observations demonstrate the effectiveness of the proposed approach in achieving good edge detection performance in situations characterized by illumination non-uniformity and low signal-to-noise ratios.

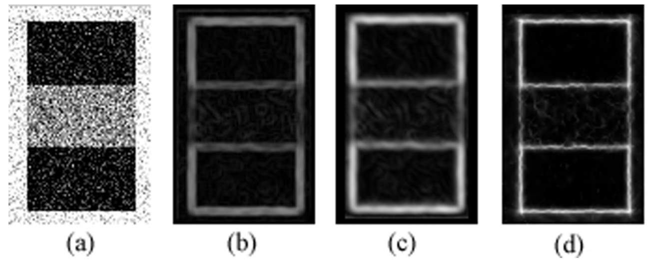

Figure 1. TEST1: a) Test image 1; edge strength maps using b) Sobel method, c) Multi-scale Roberts method, d) Proposed method

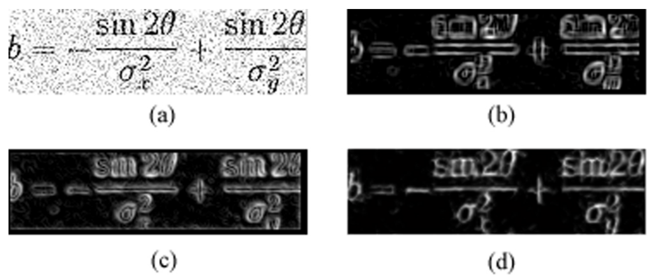

Figure 2. TEST2: a) Test image 2; edge strength maps using b) Sobel method, c) Multi-scale Roberts method, d) Proposed method

4 Conclusions

This paper introduced a novel approach to edge detection based on the non-local contributions of local frequency characteristics. By utilizing the structural characteristics of every pixel in the image, it was shown that edge detection can be qualitatively improved over existing methods on a small set of carefully chosen test images. The proposed algorithm can be integrated into a Canny edge detector to provide improved edge detection performance. Future research will investigate alternative weighting functions for determining the contributions of local frequency characteristics from non-local pixels on the estimation of edge strength to see if improved edge detection performance can be achieved on a large set of test images.

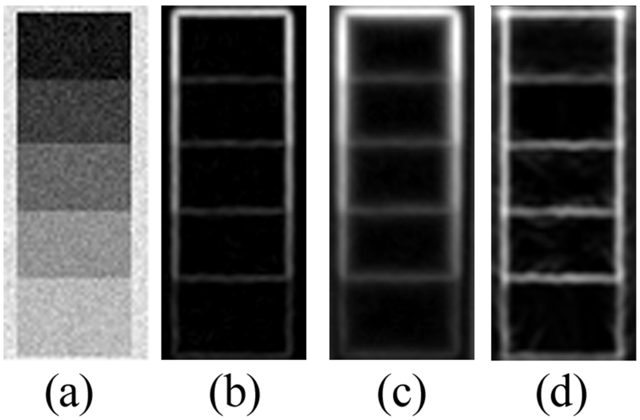

Figure 3. TEST3: a) Test image 3; edge strength maps using b) Sobel method, c) Multi-scale Roberts method, d) Proposed method

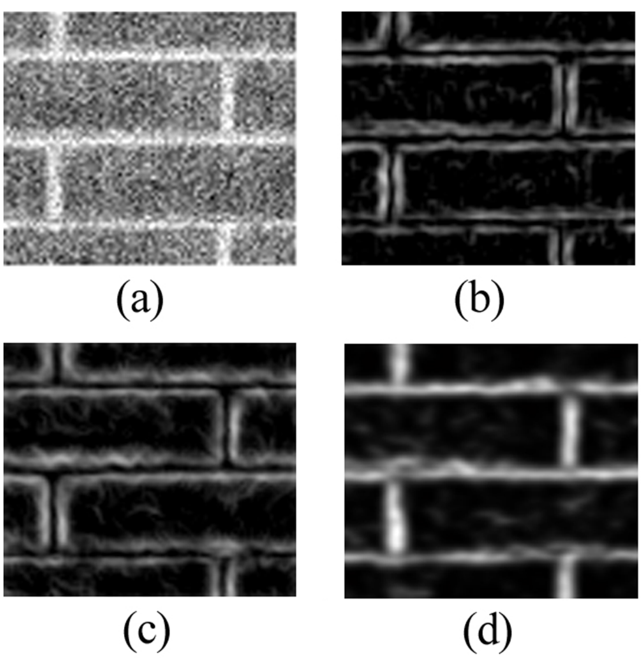

Figure 4. TEST4: a) Test image 4; edge strength maps using b) Sobel method, c) Multi-scale Roberts method, d) Proposed method

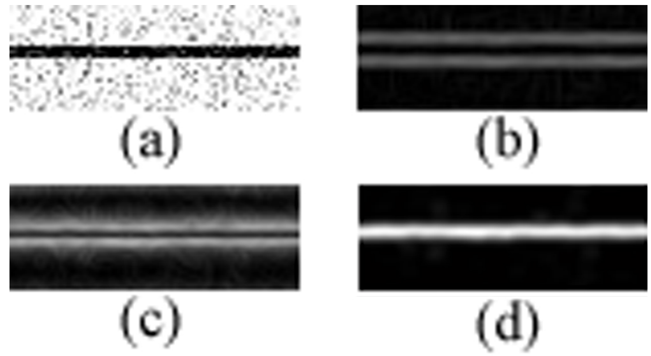

Figure 5. TEST5: a) Test image 5; edge strength maps using b) Sobel method, c) Multi-scale Roberts method, d) Proposed method

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