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Image feature detection from phase congruency based on two-dimensional Hilbert transform ☆

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ABSTRACT

The theory of phase congruency is that features such as step edges, roofs, and deltas always reach the maximum phase of image harmonic components. We propose a modified algorithm of phase congruency to detect image features based on two-dimensional (2-D) discrete Hilbert transform. Windowing technique is introduced to locate image features in the algorithm. Local energy is obtained by convoluting original image with two operators of removing direct current (DC) component over current window and 2-D Hilbert transform, respectively. Then, local energy is divided with the sum of Fourier amplitude of current window to retrieve the value of phase congruency. Meanwhile, we add the DC component of current window on original image to the denominator of phase congruency model to reduce the noise. Finally, the proposed algorithm is compared with some existing algorithm in systematical way. The experimental results of images in Berkeley Segmentation Dataset (BSDS) and remotely sensed images show that this algorithm is readily to detect image features.

1. Introduction

Feature detection is one of the most fundamental tasks in image processing. Image features such as step edges and ramps are the most valuable information that can be extracted for recognition task. Research on the algorithm of feature detection is still insufficient, even though it has been preceded for years.

Most of the pioneering algorithms of feature detection are implemented by convoluting the image with a given operator. There are many famous operators such as those developed by Roberts (1965), Prewitt (1970) and Sobel (1978). Then, Marr and Hildreth (1980) and Canny (1986) introduced more systemic algorithms to retrieve significant edges from images. Except these operators, there are different approaches which have been explored, such as active contour models (Blake, 1998) and level-set method (Sethian, 1996).

In recent years, some new approaches are developed for feature detection, such as wavelet-like filtering (Ducottet et al., 2004; Yi et al., 2009; Zhang and Bao, 2002), neural networks (Lu et al., 2003; Toivanen et al., 2003), rule bases (Bezdek et al., 1998), and fuzzy morphological concepts (De Baets et al., 1994). Even though these recent methods are claimed to have better performance than early ones, application still concern those early and simple methods.

Phase congruency method proposed by Morrone and Owens, (1987) and Morrone and Burr (1988) is an algorithm to detect features according to the phase information, and has been employed into face recognition (Bezalel and Efron, 2005), palm-print verification (Punsawad and Wongsawat, 2009; Struc and Pavesic, 2009), iris recognition (Osman, 2011) and remotely sensed image feature detection (Xiao et al., 2006; Ahmed et al., 2009). Additionally, phase congruency method has been introduced into Image quality assessment (IQA) (Liu and Laganière, 2007; Zhang et al., 2011).

Local energy model was developed by Morrone to detect image features based on one-dimension (1-D) Hilbert transform. We introduce the two-dimensional (2-D) discrete Hilbert transform to simplify the calculation of local energy, and to improve the result of feature detection. We present windowing technique in calculating the local energy, and then normalize the local energy by dividing sum of Fourier amplitude over the current window to point up features in the image. For the existence of noise, direct current (DC) component is introduced into the denominator to reduce noise.

The remainder of the paper is constructed as follows. Section 2 describes the background of previous methods in feature detection and the theory of phase congruency. Section 3 is devoted to construct 2-D local energy model based on 2-D Hilbert transform. Section 4 compares the existing algorithm with the proposed one, and presents experimental results of feature detection on images in Berkeley Segmentation Dataset (BSDS) and remotely sensed images.

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2. Background

2.1. Gradient-based feature detection methods

Pioneer gradient-based algorithms of feature detection are proposed by Roberts (1965), Prewitt (1970) and Sobel (1978). Then these methods were developed by Marr and Hildreth (1980) based on human perception. They introduced a second derivative operator Laplacian of Gaussian (LoG) with which features can be detected via the zero-crossings of the image. Canny formulated three edge detection criteria: good detection; good localization; and only one response to a single edge (Canny, 1986). Based on these criteria, Canny introduced Gaussian function, which is a low-pass filter, into the gradient-based feature detection method to reduce noise. Subsequently, Deriche (1987) and Shen and Castan (1986) developed two similar operators based on Canny's criteria. These detection operators involve a low-pass filter, such that the better detection result can be retrieved. Koplowitz and Greco (1994) fixed the error of Canny's localization criterion. Additionally, based on these classic operators, Demigny (2002) and Bao et al. (2005) did further researches to improve the performance.

Furthermore, wavelets have been used for multiscale edge analysis. Feature can be detected at the point with the local maxima of the wavelet transform. The edge detection method using wavelet is also relative to the level of intensity gradient. For example, the dyadic wavelet proposed by Mallat and Hwang (1992) is a quadratic spline by approximating the first derivative of Gaussian. The algorithm of wavelets has the same characteristic as classic operators such as Canny and Sobel operator. Namely, when the level of intensity gradient is higher, the detection from the algorithm of wavelet is more distinct.

There are two problems in gradient-based feature detection algorithm. The first problem is that these algorithms are an ideal and single model for step edge. However, there are different kinds of features such as deltas, roofs and ramp profiles. As shown in Fig. 1, Perona and Malik (1990) pointed out that image features are more a combination of steps, deltas, roofs and ramp profiles. In the general situation, features will be far more complex than Fig. 1. Thus, it is difficult to detect image features using gradient-based operator readily. The second problem is that it is easy to be influenced by the level of intensity gradient in the image. In the post-processing thresholding, edges with low level of intensity gradient may be ignored. Thus, good detection cannot be obtained before cognizing the level of contrast or the magnification of the image. Additionally, other edge detection approaches are also susceptible to gradient information, such as active contours model.

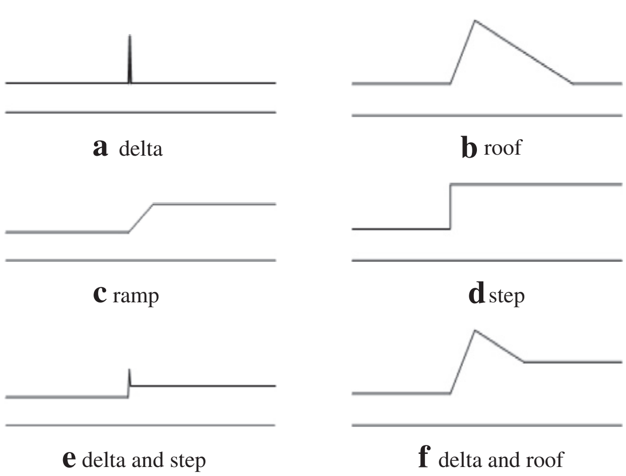

Fig. 1. Different types of image features. (a), (b), (c), and (d) show cases of delta, roof, ramp, and step; (e) and (f) show the simple situation of feature with a combination of delta and step, delta and roof.

2.2. Review of phase congruency

In the research on the phenomenon of Mach band, Morrone et al. (1986) found that there is a high phase congruency where feature can be perceived in the image. A signal can be expressed as the sum of different harmonic components using Fourier transform. Fig. 2 is a one-dimension signal with step, eight harmonic components of this signal and the sum of these harmonic components. It shows that all eight harmonic components share the same phase (the phase is zero) at the point of step. Furthermore, the principle is the same with the feature like delta, roof and ramp.

Based on the theory of phase congruency, local energy is introduced to detect features. Morrone and Burr (1988) and Morrone and Owens (1987) calculated the local energy using the original signal and its 1-D Hilbert transform, but it is not convenient that local energy is calculated by horizontal and vertical orientation, respectively. Subsequently, Kovesi (1999, 2000) developed a novel algorithm to calculate the local energy by using the odd and even log Gabor wavelet. Two variant of ε and T are introduced into this algorithm to reduce noise. T is decided by the situation of noise in the image, thus, it will involve more complex calculation. Additionally, ε can influence the detection result, and it should be more reasonable.

Morrone et al. (1986) showed the fundamental principle of phase congruency was that image features which can be perceived always relate to points with strong phase congruency in the image. For example, let $f(x) \in L^2(T)$, and the signal of $F(x)$ can be developed into Fourier series expansion which is defined by

$$f(x) = \sum_n a_n \sin(nx + \phi_{n_0}) = \sum_n a_n \sin(\phi_n(x)) \quad n \geqslant 0,\ a_n > 0, \tag{1}$$

where a_n, x and ϕ_n are the amplitude, angular frequency and initial phase of nth-degree harmonic, respectively.

When $\phi_n(x_i) = 90°$, $f(x_i)$ comes to $\sum_n a_n$, which is the sum of Fourier amplitude. For $\phi_n(x_i) = 0°$, $f(x_i)$ comes to zero. If every $\phi_n(x_i)$ of the point is the same but not 90° or 0°, the feature cannot be extracted easily. Thus, Morrone introduced Hilbert transform to determine the feature point with strong phase congruency. After Hilbert transform, the Fourier series expansion of signal has the same amplitude spectrum, and phases of negative and positive frequency component have a 90° and a −90° offset, respectively. Thus, according to Eq. (1), the Hilbert transform $\hat{f}(x)$ of $f(x)$ can be given by

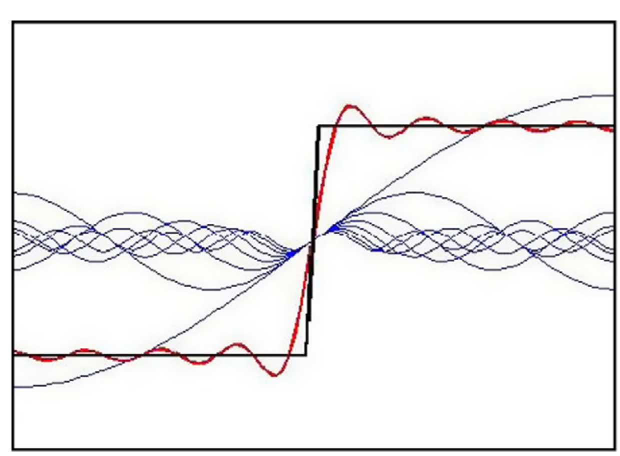

Fig. 2. Fourier series of a step feature and the sum of eight harmonic components.