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Effective and efficient contour-based corner detectors

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ABSTRACT

Corner detection is an essential operation in many computer vision applications. Among the contour-based corner detectors in the literature, the Chord-to-Point Distance Accumulation (CPDA) detector is reported to have one of the highest repeatability in detecting robust corners and the lowest localization error. However, based on our analysis, we found that the CPDA detector often fails to accurately detect the true corners when a curve has multiple corners but the sharpness of one or a few of them is much more prominent than the rest. This detector also might not perform well when the corners are closely located. Furthermore, the CPDA detector is also computationally very expensive. To overcome these weaknesses, we propose two effective and efficient corner detectors using simple triangular theory and distance calculation. Our experimental results show that our proposed detectors outperform CPDA and nine other existing corner detectors in terms of repeatability. Our proposed detectors also have a relatively low or comparable localization error and are computationally more efficient.

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1. Introduction

Detecting corners is an essential operation in many computer vision and image processing applications such as motion tracking, shape representation, image registration, camera calibration, object recognition and stereo matching. A corner can be defined as a location on an edge where the angle of the slope changes abruptly i.e. where the absolute curvature is high [1].

Corners are important features in two-dimensional (2D) images as they can represent the shape of an object very well. Therefore, corner detection plays an important role in image matching and pattern recognition. We can broadly classify the corner detectors into two groups [2] – intensity-based and contour-based. Intensity-based corner detectors [3–6] directly deal with the intensity values (or grey level pixel values) but not with the shape or any edge information of the image. On the other hand, contour-based detectors [7–12] first extract the curves (or contours) from the image by using an edge detector, and then identify the locations which have salient information or maximal curvature. Most intensity-based corner detectors are based on image derivatives that is why they are more sensitive to noise. Contour-based corner detectors, however, are generally less sensitive to noise as they are not based on image derivatives and they also apply Gaussian smoothing to remove the noises from the contours. This paper focuses on contour-based detectors as they are generally more effective compared to intensity-based detectors [2].

The Chord-to-Point Distance Accumulation (CPDA) technique [13] is a way of estimating the curvature values of 2D planar curve using a single chord. Later, Awrangjeb and Lu proposed a strong angle detector based on the CPDA technique with multiple chords and this detector is one of the best contour-based corner detectors reported in the literature [14]. This CPDA detector uses the chords, which intersect curve segments of different lengths, to estimate curvature values on each point along the curves extracted by an edge detector. The estimated curvature values of each chord are then normalized. Next, the curvature values estimated using the chords at each point are multiplied to obtain the final curvature values. Finally, points corresponding to the local maxima of the multiplied values are chosen as candidate corners and these corners are further refined to determine the final set of corners.

Although the CPDA detector is reported to achieve one of the highest repeatability and the lowest localization error among existing compatible detectors in the literature, we found that the CPDA detector has the following weaknesses. Firstly, the curvature values estimated by the CPDA detector are not proportional to the original angle of the corner. Secondly, it fails to perform well when a curve has multiple corners but the sharpness of one or a few of them is much more prominent than the rest. Thirdly, it has the potential to miss some corners on curves which have several corners closely located to each other. The second and third weaknesses are mainly caused by the process in the CPDA detector whereby the curvature values derived by the chords are combined

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to derive the final curvature values. This might cause the loss of maxima curvature values at some corner locations. Finally, the CPDA detector is computationally expensive due to the complexity of its curvature estimation and its refinement processes. How the CPDA detector works and its weaknesses will be discussed in greater detail in Sections 3 and 4 respectively.

In this paper, we have proposed two approaches for contour-based corner detection to address the potential weaknesses of the CPDA detector and various other existing contour-based corner detectors. One of the proposed corner detectors uses a simple triangular theory for curvature estimation and the other is based on the ratio of the curve length distance between two pixels to the direct Euclidean distance of these two pixels on the curve. Our proposed detectors are able to overcome all the aforementioned weaknesses of the CPDA detector. Our experimental results also show that our proposed detectors not only achieve the best repeatability and comparably low localization errors in comparison with the CPDA detector as well as the other existing compatible detectors. They are also the most efficient corner detectors.

The rest of this paper is organized as follows. A selection of the main contour-based corner detectors is described in Section 2. An overview of the CPDA detector and its weaknesses are discussed in Sections 3 and 4 respectively. Section 5 presents the proposed corner detectors. Section 6 discusses how the proposed techniques overcome the weaknesses of the CPDA detector and the complexity of the corner detectors. Finally, Section 7 presents the experimental results and Section 8 concludes the paper.

2. Related works

In this section, we discuss a selection of the main contour-based corner detectors and their weaknesses. The performance of our proposed detectors will be evaluated against majority of these detectors in Section 7.

Dominant points detectors, e.g. [15–17], are one of the earliest group of techniques which extract the strong corners from digital curves. This group of techniques refers to the locations of the strong corners as dominant points on the curve. Generally, for each candidate corner, these techniques first establish the region of supports (RoSs) which are the two sides of the corner. Then based on the RoSs, the curvatures of these candidate corners are measured. Finally, the strong corners are determined using certain rule-based or optimization algorithms. Ref. [17], proposed by Poyato, is one of the more recent and best performing techniques in this group. It establishes the RoSs using chain-code and then uses an optimization algorithm to detect the stronger corners that can still retain the general shape of the curve. This group of techniques works well if the curve representing the boundary of each object in an image can first be accurately and completely extracted. Unfortunately, this is difficult to achieve in many applications which process real images.

The Curvature Scale Space (CSS) [7] corner detector is also one of the earliest contour-based detectors. It first uses a coarse smoothing scale to estimate a curvature value for each pixel along the curve and then identifies approximate locations of the corners. Next, it uses a finer scale to track these locations to improve the localization of these corners. The main weakness of this CSS detector is in selecting an appropriate scale for identifying the approximate locations of the corners. If a coarser scale was used, the detector would be more robust to noise, but might miss many potential corners. However, if a finer scale was used, the detector would be sensitive to noise and would detect many spurious corners. The enhanced CSS [8] detector attempted to solve this weakness by using different scales for curves with different lengths. However, choosing the right set of scales for various curves' length is still difficult. The use of coarse scales on the initial step for curvature estimation is still causing high localization errors. Another weakness of these detectors is that they are not invariant to affine transformation as both detectors use the arc-length parametrization for every point on an extracted curve. Apart from these weaknesses, these CSS detectors estimate curvature values using the derivatives which are computed based on a very small neighbourhood. This makes the detectors very sensitive to the local variations and noise.

To overcome the weaknesses of the CSS detectors described above, several detectors which use multiple scales for curvature estimation at each point on a curve are proposed. Awrangjeb et al. proposed a multiscale detector (ARCSS) [11] which uses three different scales and affine-length parametrizations instead of the arc-length to detect the corners. However, this detector is computationally very expensive due to the calculation of the affine-length parametrizations. The multiscale curvature product (MSCP) [12] detector is another CSS-based detector which multiplies the curvature values derived using three scales to make the strong corners more distinguishable from the noise and weak corners. He and Yung proposed two variations [9,10] of a CSS-based detector that use an adaptive local threshold according to its neighbourhood region's curvature and then detect the angle on a proper RoS.

There are also detectors that apply other mechanisms to process the curve before deriving the corners. Zhang et al. [18] proposed a detector which applies multiple levels of Difference of Gaussian (DoG) on a curve to obtain several corresponding planar curves. These planar curves are then used for detecting the corners. Zhang's detector is reported to have higher corner detection rate compared to other CSS detectors. However, as derivative is used for curvature estimation, this detector is still sensitive to noise, thereby lowering its repeatability. Another group of detectors [19–21] applies wavelet transform to the curve to derive multiple wavelets for representing its contour orientation. However, as the wavelets acquired from wavelet transform are similar to the second derivative of the curve, these detectors can still be sensitive to noise. The last group of detectors we discuss here uses various forms of matrix manipulation, e.g. eigenvalues of the covariance matrix [22] and gradient correlation matrix [23], for processing the curve to locate the corners. Generally, these detectors are computationally highly complex due to the matrix manipulation. A more detailed review of all the techniques discussed in this section can be found in [24].

3. Overview of CPDA detector

Similar to CSS-based corner detectors, CPDA detector [14] also starts by detecting curves from the images and finding the T-junctions. Each extracted curve is smoothed with an appropriate Gaussian kernel (i.e. $\sigma = 1$, 2, or 3) depending on its length to remove the noise from it.

Next, three chords which are defined as L_i, where $i \in \{10, 20, 30\}$, are moved along each curve. In Fig. 1, let $P_1, P_2, P_3, \ldots, P_N$ be the N points on a curve. So, value i of chord L_i defines the number of points (or pixels) of the curve segment between points P_j and P_{j+i}. Chord L_i is the straight line that intersects points P_j and P_{j+i} on the curve. To estimate the curvature value $h_{L_i}(q)$ at point P_q using chord L_i, the chord is moved on each side of P_q for at most i points while keeping P_q as an

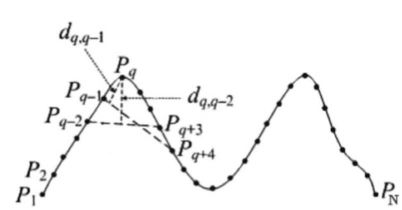

Fig. 1. Curvature estimation at a point using CPDA with chord of length L.

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