AN EFFICIENT APPROACH FOR BOUNDARY BASED CORNER DETECTION BY MAXIMIZING BENDING RATIO AND CURVATURE

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ABSTRACT

This paper introduces a novel corner detection method, which is based on the bending ratio of a moving window along with a local curvature approximation. A pre-processing step is first carried out in order to find one-pixel thin object boundaries. The proposed method traces over these boundaries, as we refer to as sub-segments and as the first step all potential corners are extracted by finding the maximum bending ratio in the moving window. The exact corner position within the window is then located accurately using the pixel-based curvature approximation. A corner factor can then be assigned to a potential corner using the maximum bending ratio and curvature values and among all potential corners, non-maximum suppression is applied to a group in close proximity and thus only the ones with the highest corner factors survive. In this way the spurious corners are significantly reduced, whilst keeping the true corners. A dedicated set of experimental results approve that the proposed method is highly accurate, computationally efficient and robust resolution and scale variations. .

1. INTRODUCTION

Corner detection is a challenging and important research area in computer vision and object recognition systems. Especially in the content-based multimedia indexing and retrieval, one of the most powerful techniques is based on shape extraction, in which corners provide significant clues in the description of an object shape. In fact two fundamental characteristics of an arbitrary object shape for visual perception are its branches (long and smooth sections) and corners where a radical change occurs on the direction of shape boundary. Therefore, the corners can be found on some particular locations where an abrupt discontinuity occurs in the direction of a smooth section.

A successful corner detector should find all the true corners with high location accuracy. Furthermore, it should eliminate or minimize all the false (spurious) corners and be robust to noise and invariant to resolution, scale and orientation. Being applicable to any arbitrary image type and computational efficiency are also important factors. Facing such challenges, considerable research work has been carried out over the years, on corner detection, and these techniques could be classified into two categories: single scale and multi-scale techniques [2]. The former ones might detect unimportant details while missing some true corners. The latter techniques could solve these problems by providing additional information about the "structural" importance of the detected corners, but the computational cost and parameters dependency are increased at the same time. Among all we particularly draw the focus on the most promising two: Harris corner detection [5], which is an improvement to the Moravec algorithm [6] and a Wavelet-based corner detection technique using the optimal scale [7]. Harris corner detection is a typical single-scale corner detection method, which uses autocorrelation as a measure of image curvature. Wavelet-based corner detection is a well-known multi-scale corner detection technique, which can present the "structural" importance of the corners in various scales. Several boundary based algorithms depending on the curvature algorithms were also reported; however they may exhibit a poor detection performance due to the noisy and instable nature of discrete (i.e. pixel based) curvature calculation.

This paper introduces a novel method for corner detection over sub-segments. We have recently proposed an elegant technique [4] for the extraction of the most relevant object boundaries, which are all one-pixel thin and continuous, by using a multi-scale sub-segment analysis. Therefore, this forms a pre-processing step for the proposed method, which can eventually be performed over the extracted sub-segments, whether in closed loop (CL) or in non-closed loop (NCL) form. Then a two-step algorithm is performed to find the potential corners first and the true ones with exact locations thereafter. The first step involves the calculation of the bending ratio within a window moving (tracing) over each sub-segment. All the potential corners with the maximum bending ratio are then subject to curvature calculation in order to detect the exact corner location within the window. Finally using the (maximized) bending ratio and curvature, the corner factor is calculated for each potential corner. The second step eliminates the spurious ones via non-maximum suppression using corner factors of the corners in a close proximity and the remaining ones are announced as the true corners.

The next section describes the details of the proposed corner detection method. Section 3 will present some experimental results. Finally, the conclusions are drawn in section 4.

2. CORNER DETECTION ALGORITHM

As Figure 1 illustrates the general overview, the proposed method is primarily designed for efficient corner detection for general purpose multimedia databases, which may contain indefinite number of arbitrary image and video clips possibly in a compressed format, with varying resolutions. All the analytical steps are performed using the luminance component of the frames extracted (decoded) either from the

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images or (key-) frames of the video clips. In order to extract (most) relevant *sub-segments* over which the proposed corner detection is applied, a certain pre-processing phase is initially performed, which mainly consists of four major parts: Frame resampling (size transformation), iterative Bilateral filtering [8] and Canny edge detection [1] to form the *scale-map*, *sub-segment* formation and analysis and finally the selection of the relevant *sub-segments* using a relevance model. Once the required number of relevant *sub-segments* are selected, then the object(s) can be extracted (see [4] for details) and the corner detector proceeds over the object boundary (CL segment) or alternatively it can proceed over the NCL sub-segments, one at a time. The details of this optional pre-processing phase can be found in [3]and [4].

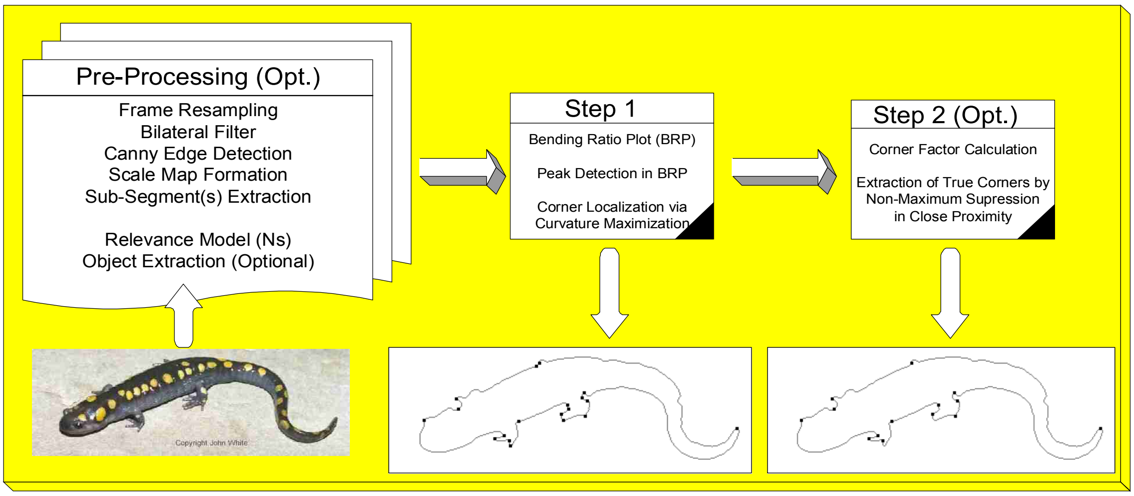

Figure 1: Overview of the proposed detector.

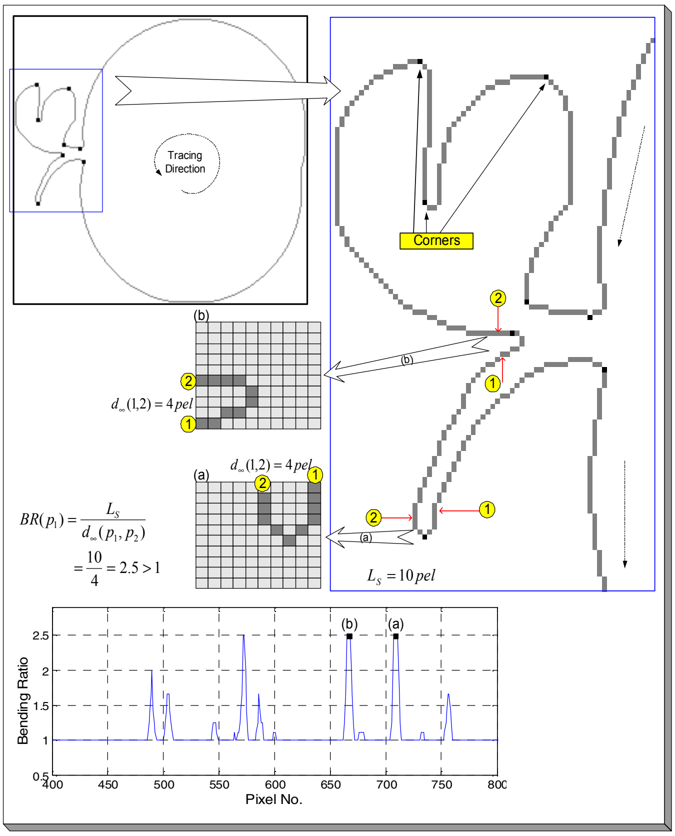

Figure 2: *BR* calculation on a sample shape for two corners (a and b) detected.

2.1. Step 1: Extraction of Potential Corners

After the pre-processing phase, the detector proceeds over each sub-segment among the list of CL or NCL sub-segment list. A moving window (*Wm*) is traced over the sub-segment from one end-point to the other and at each step, the bending ratio is calculated within the window with a certain length (i.e. L_S). Let p_1 and p_2 be the first and the last pixels of *Wm* to be examined for a corner presence. The total number of pixels is fixed for *Wm* ($N_p(p_1 \rightarrow p_2) = N_p(p_2 \rightarrow p_1) = L_S$). We define bending ratio, $BR(p_1)$, which is calculated from p_1 and can be expressed as follows:

$$BR(p_1) = \frac{L_S}{d_\infty(p_1, p_2)} \qquad (1)$$

where d_∞ represents the distance in L_∞ norm. A sample sketch of BRP for a CL segment is shown in Figure 2. On a one-pixel thick sub-segment, the bending ratio for branches (continuous and smooth sections) is either one or in the close vicinity of one. For true corners, especially for the sharp ones it starts to rise and therefore, during the tracing process we can check if $BR(p_1) > T_{BR}$, where $T_{BR} \geq 1$ is an empirical threshold, which can be set higher to detect only sharper (with smaller angle) corners in particular. Otherwise keeping $T_{BR} = 1$ will naturally indicate the presence of any (potential) corner within moving window.

In order to find the exact corner location, a discrete curvature approximation is used within the moving window. As mentioned earlier, such an approximation might be too noisy if and only the curvature is used to locate the corners over the entire object contour; however applying it within such a limited window significantly reduces its instable behavior and yields a robust estimation of the true corner location. By definition curvature in an analog curve is defined as the changing ratio of the tangent along the arc, the curvature function *κ(u)* is the derivative of the orientation function *Ø(u)* [2], expressed as in (2).

$$\phi(u) = \tan^{-1}\left(\frac{\dot{y}(u)}{\dot{x}(u)}\right) \Rightarrow \kappa(u) = \frac{\dot{x}(u)\ddot{y}(u) - \ddot{x}(u)\dot{y}(u)}{(\dot{x}^2(u) + \dot{y}^2(u))^{3/2}} \qquad (2)$$

The curvature at a given contour pixel from the positions of neighboring pixels (p-1), p, and (p+1) can be approximated as in (3):

$$\kappa(p)=\frac{(x_{p+1}-x_{p-1})(y_{p-1}-2y_p+y_{p+1})-(y_{p+1}-y_{p-1})(x_{p-1}-2x_p+x_{p+1})}{((x_{p+1}-x_{p-1})^2+(y_{p+1}-y_{p-1})^2)^{3/2}} \quad (3)$$

Once the curvature values are calculated for all the pixels within the window, the pixel with maximum curvature value is assigned as the true corner point. In case more than one pixel reaches the maxima, then the one closest to the center of the moving window of the corner, is selected. This makes sense since the center of the moving window, which yields the maximum bending ratio for this potential corner, has a high likelihood to have the corner point in a close proximity of its center. Figure 3 illustrates the curvature values ($\kappa(p)$) for the corner (a) of the sample shape in Figure 2. Note that the maximum curvature within the moving window for this corner is 2.0 and the true corner location (black pixel) is found accordingly.

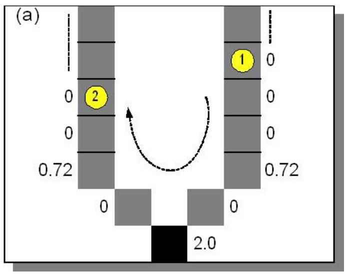

Figure 3: $\kappa(p)$ values for the sample corner (a) in Figure 2.

2.2. Step 2: Extraction of True Corners via Non-maximum Suppression

Basically in step 1, all the (potential) corners yielding a peak in BRP are detected. This is an optional step, which can post-process them and choose only the major corners among the ones that are too close for visual perception. Note that the objective of the proposed method is to detect the significant corners which play an important role in the shape characteristics. Furthermore, it is a possible consequence that a single corner can create two or more peaks in BRP, all in a close vicinity, during the sequential tracing of the moving window. Therefore, we apply non-maximum suppression in order to favor the one with highest *corner factor*, which is the dot product of the bending ratio and curvature value. Let $CF(p_C^i)$ be the *corner factor* of the i^{th} potential corner, p_C^i and can be expressed as follows:

$$CF(p_C^i) = BR(p_C^i) \times \kappa(p_C^i) \quad (4)$$

If there are n corners detected in a close vicinity (i.e. $N_p(p_C^i, p_C^{i+n-1}) < L_S$) where n>1, the only corner with highest $CF(p_C^i)$ is kept whilst the others are suppressed (deleted). Figure 1 illustrates the result of non-maximum suppression on a sample shape (CL segment). Another example can be seen in Figure 4.

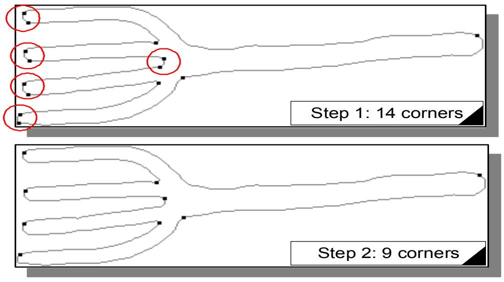

Figure 4: The effect of Step 2 on a sample shape.

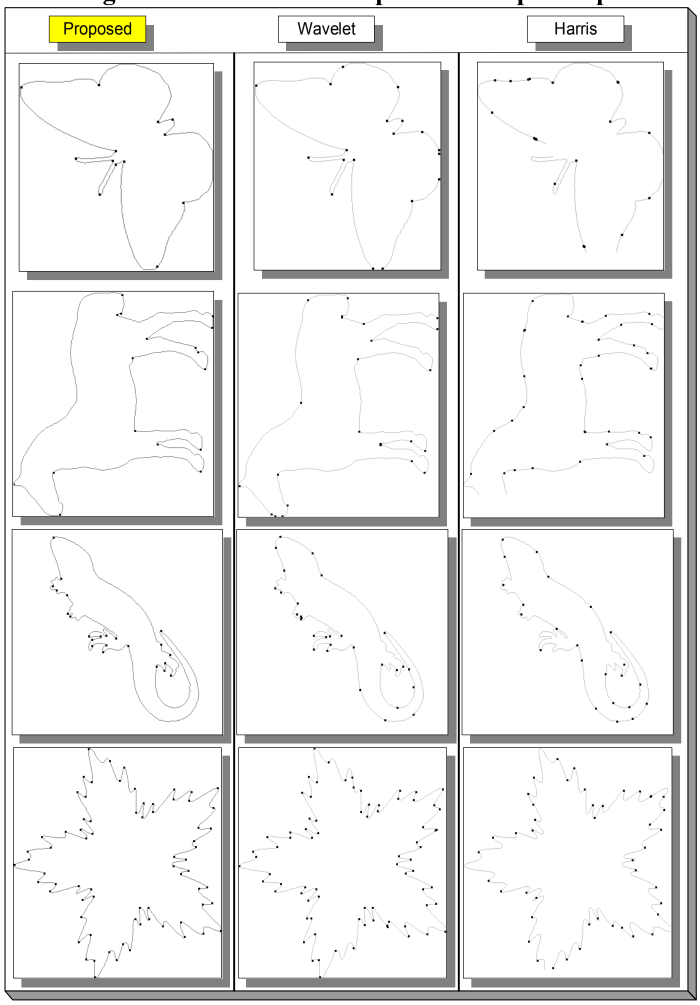

Figure 5: Comparative results for binary shapes. Black points are the corners detected.

3. EXPERIMENTAL RESULTS

In order to evaluate the accuracy and efficiency of the proposed corner detector with respect to HVS perceptive criteria (subjective test), two sets of experiments are performed over *binary* and *natural* images bearing a single object with definite corners. For binary images the optional pre-processing step is not necessary and hence entirely skipped. For comparative evaluation, we implemented wavelet-based and Harris corner detectors. Figure 5 presents the results of the three corner detection techniques over four binary shapes. As discussed earlier, the overall performance criteria depend on the following factors: detection of the true corners with good localization and avoiding the spurious (false) corners. Speed and parameter invariance are further to be considered. For Harris and Wavelet-based corner detectors we used the recommended parameters and $L_S = 10$ and $T_{BR} = 1$ for the proposed method.

The results clearly indicate that the proposed corner detector achieves the best performance in each of the four cases. It can be observed that the wavelet-based corner detector can detect most of the true corners, but it also detects some spurious ones on smooth curve segments. This is, most of the time, caused by the orientation profile which also represents global orientation changes of an object contour. It is also evident from the results that the Harris corner detector fails to detect various true corners whilst detecting several false ones due to the fact that it calculates the high curvature points directly from the original image, therefore it is quite sensitive to noise. The results of the Harris corner detector also depend significantly on smoothing and thresholding.

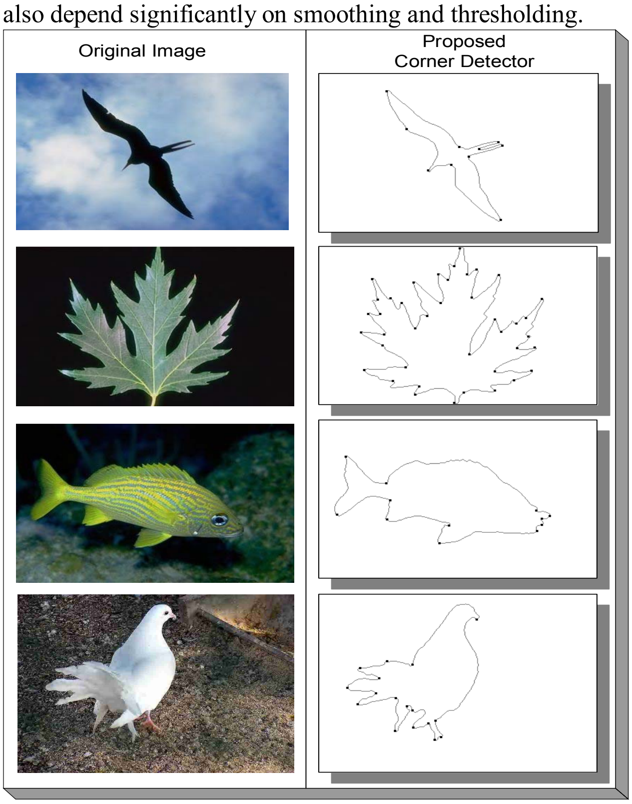

Figure 6: Proposed method applied on natural images.

Figure 6 presents the results of the proposed corner detector for four natural images with varying resolutions and in (JPEG) compressed domain. This time the pre-processing phase is applied and the object is extracted using the method in [4]. Similar to binary images, the results from natural images indicates a good detection performance.

The only major parameter in the proposed method is L_S and an extensive set of experiments performed over large set of data show that any reasonable value (i.e. $5 \le L_S \le 20$) can be conveniently used without a significant change in the detection performance. The speed of the proposed method is superior to the other two since it only performs N_S divisions and subtractions where N_S is total number of pixels in the sub-segment traced. Note that the curvature calculation is performed only within the (moving) window of a (potential) corner detected; hence such a localized calculation does not significantly affect the overall computational cost. Wavelet-based corner detection also depends on a few parameters, but the tracking process to locate real corners is quite time consuming. Meanwhile the threshold value for corner detection is needed to be investigated in different scales or even for different images. So it is quite unknown which scale should really be used for a particular image and the choice of scale can really degrades the detection performance. The performance of Harris corner detection is severely influenced by several parameters, such as the σ of Gaussian smoothing, threshold value and the local size of non-maximal suppression. Yet it has a mediocre computational complexity.

4. CONCLUSIONS

A novel corner detection technique is presented in this paper. It is a boundary based method, which can conveniently be applied over binary or natural images. For the latter case it requires a pre-processing phase in order to extract the clean and connected edge field of the object boundary, as we refer to as sub-segments. Once extracted, the method first detects all the potential corners using both bending ratio and curvature in an effective manner. Especially the noisy and instable nature of a global curvature application is avoided by using it only in a short window, to pin-point the true corner location and to determine the corner factor. An optional step can then be applied to remove the spurious corners, which occurs in a close proximity. In this way only the major corners with the highest corner factors remain, as intended.

The comparative evaluation against two well-known detectors clearly indicates the superiority of the proposed method in terms of accuracy, efficiency and robustness. Yet we observed that one or few pixels offset can occur as a result of discrete curvature approximation, which is calculated only from the two neighbor pixels. Current and planned research work therefore includes: adapting *k*-curvature with an extended (size *k*) window and investigate further measures along with the bending ratio to detect smoother corners. Modeling major and minor corners with respect to HVS is also considered.

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