AN IMPROVED WAVELET-BASED CORNER DETECTION TECHNIQUE

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ABSTRACT

In this paper an improved, wavelet-based technique for corner detection, in 2-D planar curves, is presented. This boundary based technique is simple to implement and computationally efficient and exploits wavelet transform modulus maxima (WTMM) to detect corners. The proposed algorithm is robust with respect to object geometry. We also report results under AWGN noise.

1. INTRODUCTION

Corners in digital images give important clues for shape representation and analysis [1]. A multiresolution representation provides a simple hierarchical framework for interpreting the input image information [2]. In the literature, scale-space based approaches are usually proposed for developing multiscale corner detection algorithms [3, 4, 5, 6]. However, these techniques are not computationally efficient because they require filtering with Gaussian function over continuous scales. Wavelet theory provides a unified framework for a number of techniques which had been developed independently for various signal processing applications.

Several corner detection techniques [7, 8] have been proposed in the literature. In [7] derivative of the Gaussian function is used as wavelet. However, the derivative of the Gaussian is not orthogonal and fast computational algorithm for dyadic decomposition does not exists. In [8] a fast wavelet (given by Mallat [9]) is used to detect corner in 2-D planar curves. However, this technique requires splitting the orientation profile and computing derivative of the ratios of the wavelet transform modulus maxima (WTMM). Here we propose a wavelet based algorithm which does not require these complex steps.

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2. CHOICE OF WAVELET

Let the input signal is rewritten as $D = (S_1 f(n))_{n \in \mathbf{Z}}$. Let us denote

$$W_{2^j}^d f = (W_{2^j} f(n+\omega))_{n \in \mathbf{Z}} \tag{1}$$

and

$$S_{2^j}^d f = (S_{2^j} f(n+\omega))_{n \in \mathbf{Z}} \tag{2}$$

where ω is the sampling shift that depends only on the wavelet $\psi(x)$. For any coarse scale 2^J, the sequence of discrete signals

$$\left\{ S_{2^J}^d, \left(W_{2^j}^d f \right)_{1 \le j \le J} \right\} \tag{3}$$

is called the *discrete dyadic wavelet transform* of $D = (S_1 f(n))_{n \in \mathbf{Z}}$.

From the discrete wavelet transform, at each scale 2^j, modulus maxima is detected by finding the points where $| W_{2^j} f(n+\omega) |$ is larger than its two closest neighbor values and strictly larger than at least one of them. The abscissa $n+\omega$ and the value $W_{2^j} f(n+\omega)$ at the corresponding locations are recorded.

A remarkable property of the wavelet transform is its ability to characterize the local regularity of functions [10]. In mathematics, local regularity is often measured with Lipschitz exponents. In [9], Mallat and Zhong proved that Lipschitz regularity can be accurately measured from WTMM if the wavelet used is derivative of the Gaussian. They also proposed a quadratic spline wavelet which is computationally efficient and quite similar to the derivative of the Gaussian. These properties make this wavelet a good choice for corner detection application.

3. CORNER DETECTION SCHEME

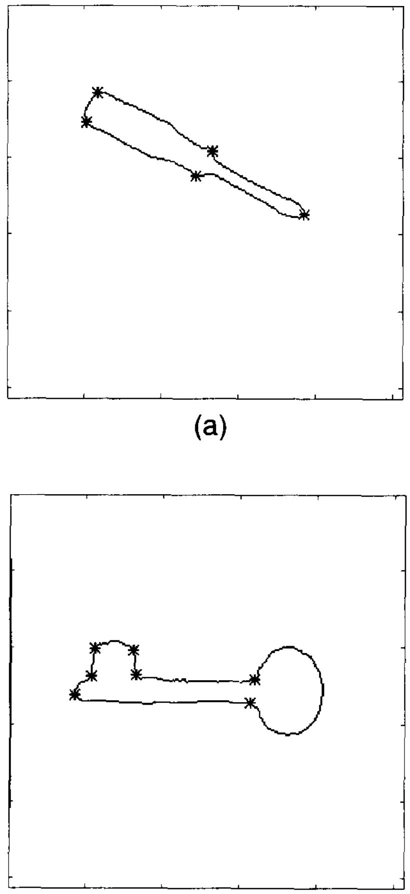
The preprocessing steps are done as discussed in [8]. This preprocessing gives orientation profile (orientation of the tangent along the boundary contour) from the input image. Lee *et al.* [11] presented an analysis of the behavior of wavelet transform modulus maxima with different corner models. They also used derivative of the Gaussian as the wavelet function. Based on their analysis, a simple and computationally efficient algorithm is developed.

Corners and arcs are relative terms and largely depend upon the shape of the object under consideration. If there are sharp corners at the boundary, smooth curvature changes will not be recognized as corners. On the other hand, if the shape consists only of smooth curvature changes then these curvature changes will be recognized as corner points. In order to provide such robustness, this algorithm starts with the normalization of wavelet transform modulus maxima. This normalization is obtained at each level with the global maxima of that level. This normalization also makes algorithm suitable when some other wavelet is to be used for analysis. This normalization is done in **Step 1** of the algorithm.

Step 1:
Orientation profile is decomposed using wavelet transform at scales 2^1, 2^2, 2^3 and 2^4. Wavelet transform modulus maxima (WTMM)is computed at each of these levels. These WTMMs at each level are normalized with respect to the maximum peak at that level.

Step 2:
The events (valid corners) are observed at the highest scale (2^4). The peaks higher than some threshold τ_1 are recognized as valid events. These events are successively tracked at lower scales (2^3, 2^2, 2^1) to find their exact locations.

Step 3:



(a)

(b)

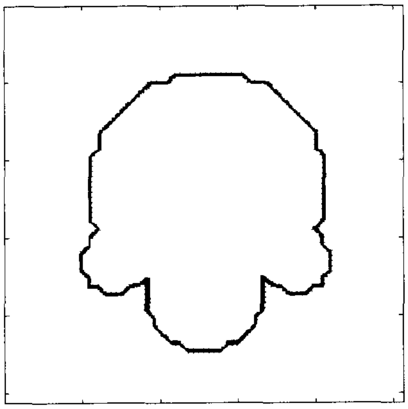
Figure 1: Corner detection Results

Those events which are increasing at decreasing scales and are greater than some threshold τ_2 ($< \tau_1$) at scale 2^4 are also taken as valid events. These events are also successively tracked at lower scales ($2^3, 2^2, 2^1$) to find their exact locations.

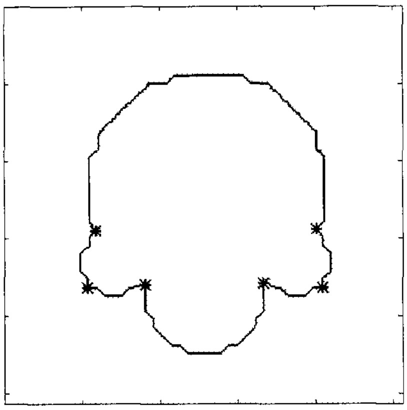
Step 4:
Find a large (greater than some threshold τ_3) events in the vicinity of already detected events in the previous steps from the lowest scale (i.e. 2^1).

4. RESULTS AND DISCUSSION

The result of corner detection using the proposed scheme is shown in Fig. 1, where $\tau_1 = 0.4$, $\tau_2 = 0.1$ and $\tau_3 = 0.65$. These values of threshold are found after



(a)



(b)

Figure 2: Corner detection Results (a) Test Image (b) Detected corners

testing the algorithm with a large number of images. We used the similar images used by others such as by Asada and Brady [5] (Fig. 1(a)), Lee et. al [8] (Fig. 1(b)) and Rattarangsi and Chin [3] (Fig. 2(a)). Here we observe that the performance of the proposed technique is better, or at least the same as the one presented in the literature.

As far as computational efficiency is concerned, the technique reported by Asada and Brady [5] is time consuming because it requires computing decompositions using both first and second derivatives of the Gaussian function. These derivatives are not orthogonal and fast computing algorithm for descrete dyadic wavelet transform does not exists. The technique presented in [8] is computationally complex because it requires taking derivative of the ratio of wavelet transform modulus maxima and then splitting the orientation profile to detect corners. The proposed technique does not requires these complex steps. Hence, the proposed technique is computationally efficient and simple to implement. We also performed corner detection tests under AWGN noise. Noise was added in the coordinates of the tracked boundary. We performed corner detection tests with different standard deviation (σ_N) of Gaussian noise. These results are shown in Fig. 3.

5. CONCLUSIONS

Here a wavelet based scheme is presented for the detection of corners in 2-D planar curves. We observed that the proposed method gives competitive results with respect to the other available techniques. The proposed technique has the advantage that it is computationally inexpensive when compared with the other techniques available in the literature. It also performs well under AWGN noise. Moreover, the proposed algorithm is robust with respect to object geometry and the type of the wavelet used for the decomposition.

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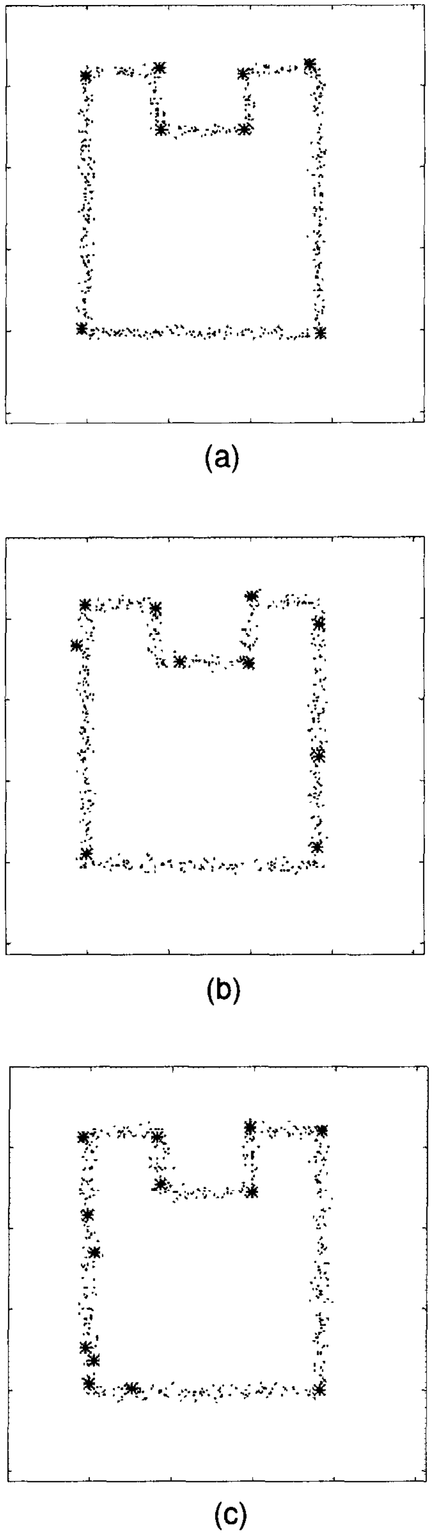

Figure 3: Corner detection Results under noise (a) $\sigma_N = 2.82$ (b) $\sigma_N = 3.59$ (c) $\sigma_N = 3.85$

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