WAVELET TRANSFORM BASED FEATURE DETECTION

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ABSTRACT

This paper presents a new method of the local image feature detection. The method is based on a corner detection on top of a stationary wavelet transform. The point of this method is that the corner detector is applied on partial derivatives obtained from the wavelet transform. Thus, edges are obtained at different scales. A position of the detected corner can be estimated with sub-pixel accuracy. The proposed method can be used as part of a robust feature extractor.

1 INTRODUCTION

The feature detection is widely used in the computer vision. Purpose of such detection is to locate some characteristic singularities like corners or blobs. That detection should be invariant at least to an image rotation and scale, and an intensity change. Another requirement can be a good accuracy and stability, as well as a low computational complexity. Such detection is often used in a conjunction with the feature descriptor extraction. Commonly used methods for that feature detection and extraction include the SIFT [6] and the SURF [7] algorithms.

This paper presents an image interest points detection method based on the stationary (undecimated) wavelet transform [1]. That transform can be understood as multiple scale image representation which consists of low frequency and high frequency coefficients. Moreover, the wavelet transform can be seen as multi-scale differential operator [1]. Hereafter, the Harris operator [5] is now used as tool for an edge and corner detection in such image component. This operator is actually based on the partial derivatives of analyzed image.

2 WAVELET TRANSFORM

The wavelet transform [1] [2] [3] allows to obtain a time-frequency description of a signal. This paper assumes the reader familiar with the wavelet transform.

The stationary wavelet transform (SWT) is designed to shift-invariant discrete signal analysis. In one step of decomposition, the SWT will produce two signals of same length. These signals are called the approximation and detail coefficients. Unlike the discrete wavelet transform (DWT), these coefficients are not downsampled. Instead of doing this, decomposition filters are upsampled before the next step of decomposition. The dyadic decomposition is often used. That means that there is inserted a “zero” between every two filter coefficients from the previous decomposition scale. It is the same like placing $2^j - 1$ zeros between filter coefficients from the first scale. This algorithm [1] is often called "*algorithme à trous*" in French. Computing the discrete wavelet transform by convolution would waste a computation time. The lifting scheme [4] is a fast implementation of this discrete dyadic wavelet transform. There are lifting scheme for stationary wavelet transform also.

In two dimensions the discrete wavelet transform is defined analogously [1] [3]. At the Figure 1 is depicted a test image and its fourth level of decomposition (a wavelet modulus is shown). Using the SWT to a two-dimensional signal (i.e. an image) will produce four series of coefficients of same size as former signal in each decomposition level. Consequently, the SWT will create j four-tuples of coefficients for j levels of decomposition. Coefficients on each scale 2^j and position (x,y) are denoted as $a_j(x,y)$ for approximation coefficients, $h_j(x,y)$ for horizontal edges, $v_j(x,y)$ for vertical edges and $d_j(x,y)$ for diagonal edges.

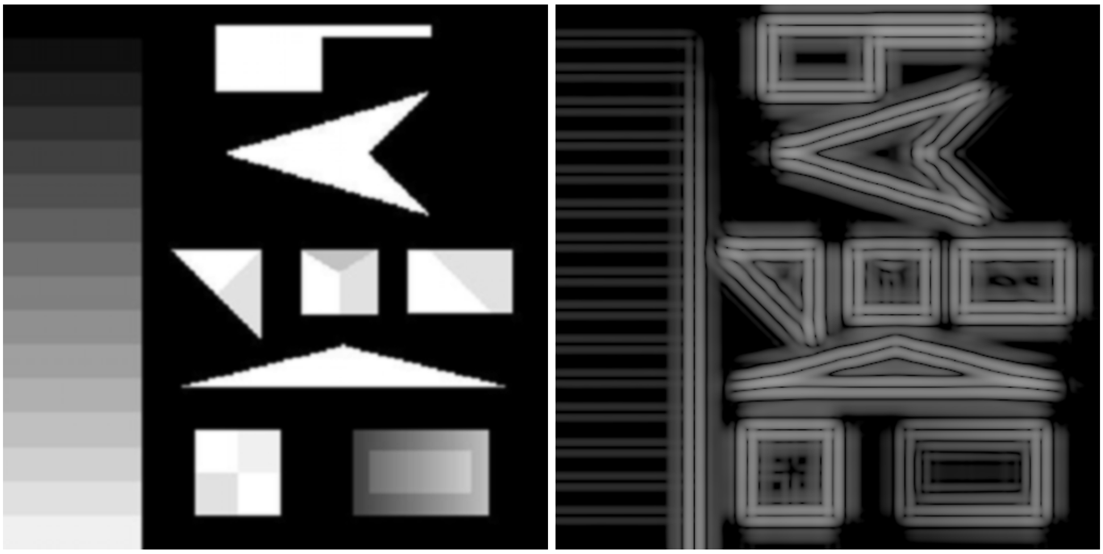

Figure 1: A test image (left) and its wavelet transform modulus at scale 2^4 computed with the biorthogonal spline wavelet 4,4 (also referred as 9/7, right).

3 CORNER DETECTION

Purpose of the corner detector is to identify some points of interest like corners, and not like edges. Such detection should be invariant at least to a rotation, a scale and an intensity change. The Harris corner detector algorithm [5] is defined as follows. Let I be a source image. The autocorrelation matrix

$$A(x,y) = \begin{bmatrix} \frac{\partial I(x,y)}{\partial x}\frac{\partial I(x,y)}{\partial x} & \frac{\partial I(x,y)}{\partial x}\frac{\partial I(x,y)}{\partial y} \\ \frac{\partial I(x,y)}{\partial x}\frac{\partial I(x,y)}{\partial y} & \frac{\partial I(x,y)}{\partial y}\frac{\partial I(x,y)}{\partial y} \end{bmatrix} * w \tag{1}$$

is computed for each pixel (x,y). The elements of this matrix are partial derivatives of I in direction of a variable x or y; $*$ symbol denotes the convolution operator and w is the Gaussian window. The Harris operator now constructs a cornerness map from the equation 1 for each (x,y) as

$$C(x,y) = \det(A(x,y)) - \kappa \,\mathrm{trace}^2(A(x,y)). \tag{2}$$

The constant κ is defined empirically. Good values are between 0.03 and 0.15. In next step, the cornerness map is thresholded. All values below a threshold T are set to zero. The threshold value is also defined empirically. Finally, the local maxima points are found.

4 PROPOSED METHOD

An image decomposition using the SWT produces matrices of $a_j(x,y)$, $h_j(x,y)$, $v_j(x,y)$ and $d_j(x,y)$ coefficients for each scale 2^j, where (x,y) is the point position and j denotes a decomposition level. For feature detection it is important to employ a symmetric compactly supported wavelets. These wavelets have a linear phase. This means that there is no shift between a detected singularity and a corresponding response in a wavelet coefficient. To avoid the growth of energy at every next scale, the filter coefficients normalized by factor of $1/\sqrt{2}$.

The wavelet with k vanishing moments can be seen as a multi-scale differential operator [1] of order k. In consequence of that property, the wavelet transform can easily detect edges and corners. In this paper the biorthogonal spline wavelet [2] (also called the Cohen-Daubechies-Feauveau wavelet) 4,4 (of length of 9/7) is used. This wavelet has 4 vanishing moments. Therefore, it is a differential operator of order 4. Detailed coefficients, h and v, are thus partial derivatives or order k in direction of x and y, respectively. Thereafter, d coefficients are derivatives in direction of x followed y or vice versa.

The key idea of the proposed method is to use these partial derivatives for autocorelation matrix construction (see section above). The autocorrelation matrix for each (x,y) at each scale 2^j is now given as

$$A_j(x,y) = \begin{bmatrix} h_j(x,y) & d_j(x,y) \\ d_j(x,y) & v_j(x,y) \end{bmatrix}. \tag{3}$$

In that equation the square of derivatives as well as the Gaussian window weighting is omitted because it appears to be negligible. The Harris operator now constructs the cornerness map as in the equation 2. In this paper $\kappa = 0.14$ constant has been used. Afterwards, the cornerness map at each scale is thresholded in order to remove edges and a noise. That is, all points with value below a universal threshold T are discarded. Finally, a non-maxima suppression is now performed. Note that an another corner detector can be used instead of the Harris operator. The interest points are found with a sub-pixel accuracy by interpolation of cornerness map.

In conclusion, described approach is able to find corners and blobs in different scales employing partial derivatives of a smoothed image. The method is parameterized by the κ constant and the T threshold. Furthermore, the proposed method can be extended to describe the resulted interest points. These feature vectors (descriptors) can be extracted similarly to the SIFT [6] or the SURF [7] algorithms. For fast computation of these vectors can be used a image at the scale j represented by a_j coefficients.

5 COMPARISON

The proposed method has been compared with the SURF algorithm on an image displayed in the Figure 1. Detected corners are shown in the Figure 2. Size of circle is proportional to the scale. Properties of a valid detection depends on a selected wavelet and parameters of the Harris operator. In the case of proposed method, $\kappa = 0.14$ parameter has been used (see the equation

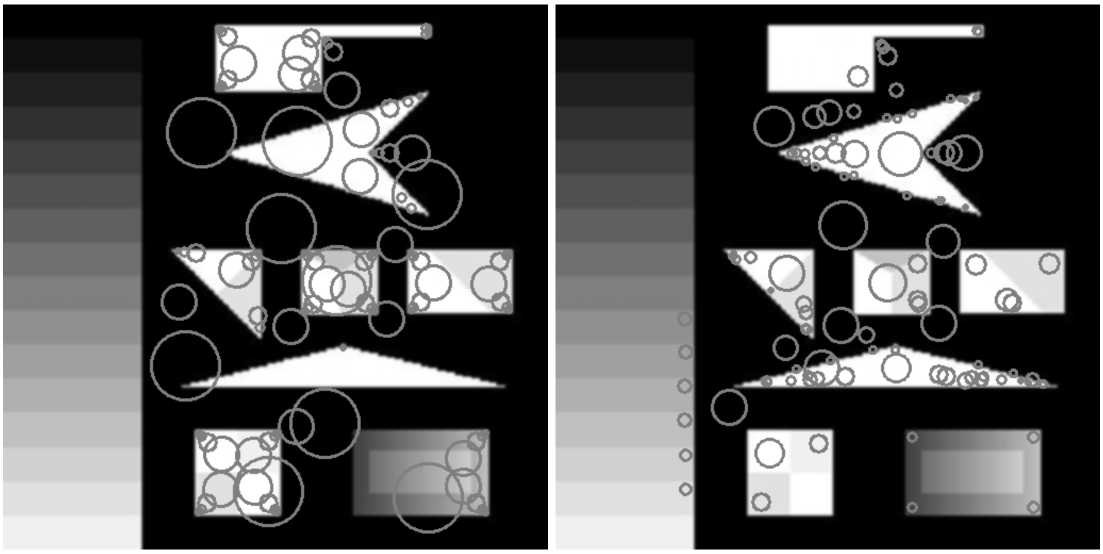

Figure 2: The proposed method (left) and the SURF algorithm (right). Both cases with similar count of detected points (105 in the case of the SURF and 109 in the case of the proposed method).

2). Corners has been detected up to a scale of 2^7, and except for a scale of 2^1 (because of the sensitivity to noise). The applied threshold has been set to 256. In the case of the SURF method, the Hessian threshold has been set to 1500. Mentioned parameters has been chosen in order to similar count of detected points and also for an image clarity. Note that the version of the SURF method was used as implemented in the OpenCV 2.0 library.

The Figure 2 shows characteristics of the proposed method. The method detects points of interest in similar locations (inside corners and blobs) as the SURF method. It seems to be less susceptible to detection of points along edges. Important property of an interest point detector is repeatability. Comparison of this property should be subject of future work. Furthermore, the detected points can be found with a sub-pixel accuracy. The computational complexity of a two dimensional SWT is $O(N^2 logN)$.

6 CONCLUSION

The method of the multiscale interest point detection based of the stationary wavelet transform has been presented. To properly determine the position of the detected singularity it is important to use symmetric compactly supported wavelets [2]. Such transform can be computed by fast algorithms [4]. A behavior of proposed method depends on a chosen wavelet as well as κ constant and T threshold. The further work should focus on appropriate parameters investigation and objective comparison with commonly used approaches like the SURF algorithm.

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