Multi-resolution Optical Flow tracking algorithm based on Multi-scale Harris Corner points feature

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Abstract: Multi-resolution optical flow tracking algorithm decomposes the object displacement in the wavelet pyramid, then sparse optical flow based on LK (lucas-kanade) algorithm matches the object feature in all the level of the wavelet pyramid step by step. Steadily tracking rapid motion objects is achieved. As to the feature of motion vehicles, multi-scale Harris corner detection based on wavelet is proposed. Traditional Harris corner detection about omitting corner point and asymmetrical array is improved. It is suitable to extract motion vehicle feature in complicated traffic scene. With the experiment, it can be verified that the corner point is always steady and reliable when the vehicle is turning and moving, and the camera is zooming in and out. The tracking algorithm also can accurately match the feature points with the high real-time performance.

Key Words: Optical flow, Wavelet pyramid, Tracking, Harris corner detection, Multi-resolution

1 INTRODUCTION

Motion object tracking technology is currently one of the most active research topics in the domain of computer vision. Optical flow is the important method to research tracking problem, so it is always paid attention to by researchers. For example, K. Kiratiratanapruk et al. researched the sparse optical flow field based on LK algorithm of the motion object region in the traffic monitoring system, and tracking the motion vehicles is achieved[1]. There are some classical algorithms of optical flow, for instance, Horn and Schunck algorithm based on global smoothness constraint, D. J. Fleet algorithm based on phase information and D. J. Heeger algorithm based on energy information and so on. The robust and effect of D. J. Fleet algorithm and D. J. Heeger algorithm are better than others, but they are more complicated and can not meet the requirement of real-time system[2]. However, Horn and Schunck algorithm is simple, but its global smoothness constraint coerces the optical flow field to be smooth in the edge region, the speed of which always sharp changes, so the edge shape of the object easily distorts[3][4].The complication and tracking effect of sparse optical flow based on LK algorithm are satisfying, but when the object rapidly moves, the stability of LK algorithm will become bad and even tracked object will be lost[5][6]. Therefore, by analysing the limitations of sparse optical flow based on LK algorithm multi-resolution optical flow tracking algorithm based on wavelet pyramid is proposed to solve the problem of tracking rapid motion objects. And according to the feature of motion vehicles, multi-scale Harris corner detection based on wavelet is proposed.

2 TRACKING ALGORITHM BASED ON OPTICAL FLOW

2.1 LK Sparse Optical Flow Tracking Algorithm

In an image neighborhood W which contains texture information, the optical flow residual function ε is defined as follows [7]:

$$\varepsilon = \iint_W [I_{t+1}(x-d_x, y-d_y) - I_t(x,y)]^2 dxdy \tag{1}$$

$I_t(x,y)$ is the greyscale value of the image is the location *(x,y)* at t time. $D=[d_x \quad d_y]^T$ is the image displacement at the location *(x,y)* during unit time. In essence, the goal of LK algorithm is to get the *D* between two close frames, and the result D_{opt} is got when the optical flow residual function ε is minimized. So by the Taylor expansion the $I_{t+1}(x-d_x, y-d_y)$ becomes:

$$I_{t+1}(x-d_x, y-d_y) \approx I_{t+1}(x,y) - [I_x \quad I_y]D \tag{2}$$

And when the derivative of ε is zero, the optimum result is obtained: $D_{opt} = G^{-1}b$ (3)

Spatial gradient matrix: $$G = \iint_W \begin{bmatrix} I_x^{\,2} & I_x I_y \\ I_x I_y & I_y^{\,2} \end{bmatrix} dxdy \tag{4}$$

Image mismatch vector: $$b = \iint_W \begin{bmatrix} \delta I \ I_x \\ \delta I \ I_y \end{bmatrix} dxdy \tag{5}$$

I_x *and* I_y are the partial derivative of $I_{t+1}(x,y)$ at the direction of *x and y* and δI is the difference of two close frames at the location *(x,y)*.

According to equation (2), the condition of the Taylor expansion will be met only when the *D* is small enough. So the tracking will fail, when the speed of object is high and the displacement *D* between two close frames is too large. This is the limitation of the LK algorithm. Based on the idea of Multi-resolution tracking, *D* is decomposed to some small displacements in the wavelet pyramid, and the

978-1-4244-1734-6/08/$25.00

small displacement meets the requirement of the LK algorithm.

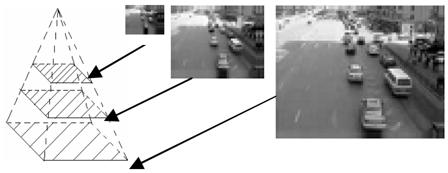


Fig. 1 three level wavelet pyramids

2.2 Multi-resolution optical flow tracking algorithm based on wavelet pyramid

Multi-resolution optical flow tracking algorithm based on wavelet pyramid decomposes D to some small displacements in the wavelet pyramid, then the optimum result D_{opt} will be got by a series of optical flow iterative algorithm in the level of wavelet pyramid and displacement transfer between the two close levels. The structure of the wavelet pyramid (see Fig.1) comprises the approximate coefficient of the image. The top level is the highest scale approximate coefficient, and the bottom level is the lowest one.

Every frame is to be wavelet transformed by Mallat algorithm and sym4 wavelet function. Because of the 2 scales down-sampling of Mallat algorithm, the proportion of two close level image size is 4:1, and proportion of the displacement is 2:1.

The wavelet pyramid is adopted, so the optical flow residual function ε becomes:

$$\varepsilon^L = \iint_W (I_{t+1}{}^L(x+g_x{}^L+d_x{}^L, y+g_y{}^L+d_y{}^L) - I_t{}^L(x,y))^2 dxdy \tag{6}$$

$g^L = [g_x{}^L, g_y{}^L]$ is the displacement transfer vector between the close levels, and the initial value of g^L is $g^{L_{top}} = [0 \quad 0]^T$. It is constant when the optical flow is computed in the level. $D^L = [d_x{}^L, d_y{}^L]$ is the accumulative displacement vector in the level. It is got by accumulating the results of optical flow iterative algorithm.

The detailed steps of the multi-resolution optical flow tracking algorithm based on wavelet pyramid are as follows:

Firstly, the optical flow is iteratively computed in the top level L_{top}, until the result D_i is less than the threshold. D_i is accumulated: $D^{L_{top}} = \sum D_i$.

Secondly, $D^{L_{top}}$ and $g^{L_{top}}$ are brought to the next level L_{top-1}, then the first step is redone and $D^{L_{top-1}}$ is got. Because of the 2 scales downsampling of the Mallat algorithm, $g^{L_{top-1}} = 2(g^{L_{top}} + D^{L_{top}})$ (7)

At last, the first step is done in every level of the pyramid until the lowest level L_{bottom}. And finally D_{opt} is got.

$$D_{opt} = g^{L_{bottom}} + D^{L_{bottom}} \tag{8}$$

The flow chart of the Multi-resolution optical flow tracking algorithm based on wavelet pyramid (see Fig. 2):

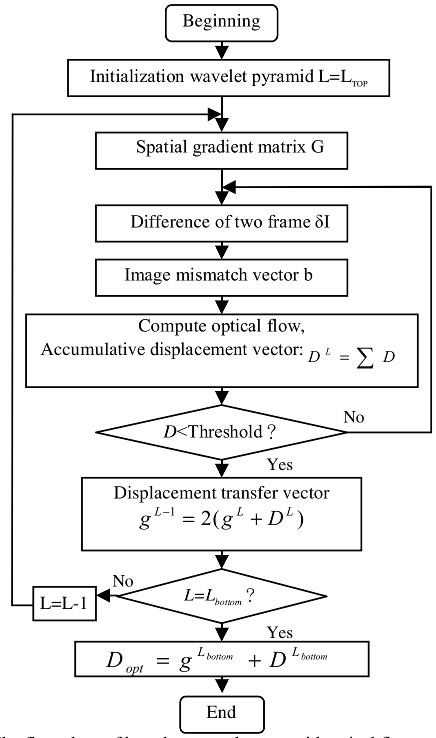


Fig 2. The flow chart of based on wavelet pyramid optical flow

Assuming that each elementary optical flow computation step can handle pixel motions up to $D_{\max}$, then the overall pixel motion that the pyramidal implementation can handle becomes $D_{\max\_overall} = (2^{L_{top}+1} - 1)D_{\max}$. For example, for a pyramid depth of L_{top} = 3, this means a maximum pixel displacement gain of 15.

3 CORNER POINT FEATURE EXTRACTION

LK algorithm computes the motion vector in the direction of the motion object image gradient[8]. So tracking is the steadiest when the directions of velocity and gradient of the motion object image are the same. This characteristic decides the principle of the feature extraction, so the corner point is a good tracking feature of LK algorithm[5].

There are some advantages of Harris corner detection, such as simple computation, invariability of rotation and motion. But traditional Harris corner detection only can be done within the single scale, and the results of detection overly depend on the threshold. If the threshold is too large, some corner points may be lost. However, if the threshold is too small, some fake corner points will be detected. So the lack of invariability of scale function depresses the performance of the Harris corner detection algorithm. At the same time Harris corner detection may lose some real corner points on the region of gradient changing smoothly. Furthermore, it is sensitive to noise.

The matrix of Harris corner detection:

$$M = \sum_{\Omega} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} w(x, y) \tag{9}$$

w(x,y) is a Gauss window function. Ω is the 3×3 neighbourhood. When both λ_1 *and* λ_2, which are the two eigenvalues of *M,* are larger than the threshold, the point is just a Harris corner point. Our tracked objects are the motion vehicles in the traffic scene. Because the region of tracked objects is small at the initial tracking, the number of the Harris corner points is small and its distribution is not symmetrical. If a lot of corner points are occluded or lost, the tracking will fail. So multi-scale Harris corner detection based on wavelet is proposed. With the quality of corner points unchangeable, it can increase the number of corner points and make their distribution more symmetrical.

Because the approximate coefficients of image wavelet transform mainly comprise the low-frequency information, the contour of the objects is reinforced, and the number of corner points in the contour of objects will increase. However, the detail coefficients mainly comprise gradient information of the image, so it is of advantage to find the corner points on the detail gradient of the objects. The approximate coefficients and detail coefficients can complement each other.

The detailed steps of multi-scale Harris corner detection algorithm based on wavelet are as follows:

Firstly, sym4 wavelet function is adopted to decompose the image by the Mallat algorithm. The symmetry of sym4 can improve the quality of the reconstruction image.

Secondly, two corner detection pyramids are constructed. One consists of three scale approximate coefficients; the other consists of three scale reconstruction image of detail coefficients.

Thirdly, Traditional Harris corner points are detected in the two pyramids and the results are put into two candidate feature subsets. Because of the smoothness of the wavelet transform, the window function is set to be constant *w(x,y)*＝1.

At last, by searching all the corner points of the two candidate feature subsets, the final corner points are confirmed. The principle of the confirmation is that after the top level corner subset of pyramid C_{top} is confirmed, corner points are searched in the neighbourhood of C_{top}, which is in the next level subset. If the corner points are found in the next level, they are reserved, otherwise discarded. The above steps are repeated, until the bottom level. In the end, the two candidate feature subsets are incorporated, after overlapping corner points are deleted.

The flow chart of multi-scale Harris corner detection based on wavelet (see Fig. 3):

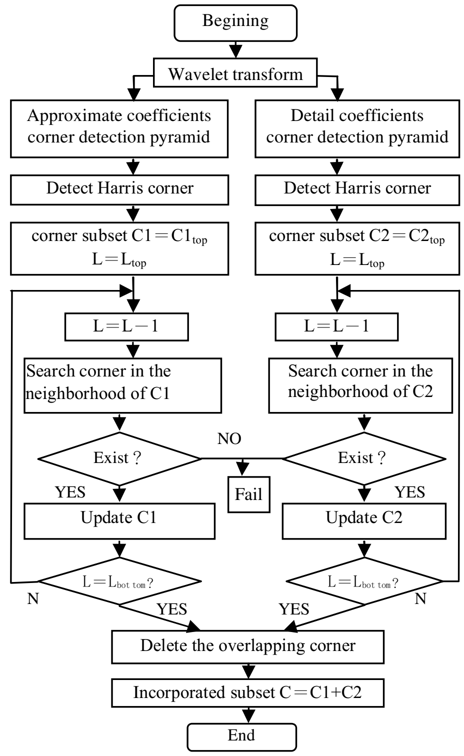


Fig3. Flow chart of multi-scale Harris corner detection based on wavelet

4 THE RESULT OF EXPERIMENTATION

In order to confirm the validity of the algorithm, a car which is turning right at a crossroad is tracked. Corner points of the car are detected by multi-scale Harris corner detection algorithm based on wavelet in the first frame, then all the feature corner points are tracked by the multi-resolution optical flow tracking algorithm based on wavelet pyramid. Corner detection results (see fig.4, fig.5 and fig. 6(b)):

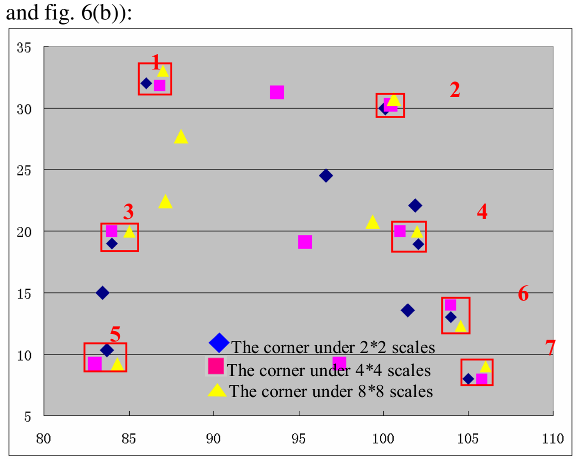


Fig 4. Corner detection based on three scale approximate coefficients

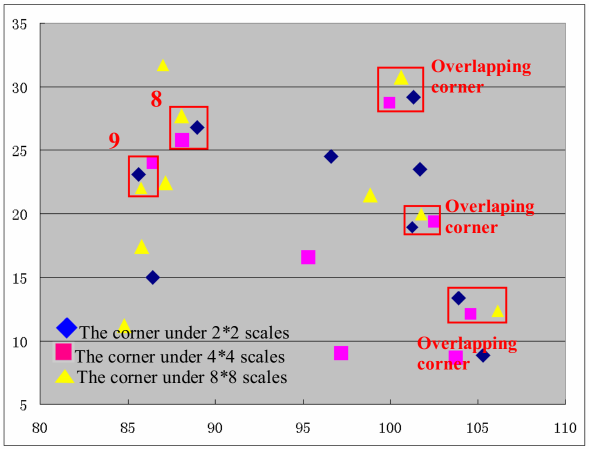


Fig 5. Corner detection based on three scale detail coefficients

Seven corner points are detected in the pyramid of approximate coefficients. However, five corner points are detected in the pyramid of detail coefficients. The corner points in the approximate coefficients are mainly located on the contour of the car. In the detail coefficients, there are five corner points, and three of them are overlapping corner points.

The two corner detection pyramids can complement each other, so the number of the omitted corner points is reduced. Moreover, the location is more accurate, because of the invariability of scale. The conclusion can be drawn from the Fig.6 (a), (b) and TABLE I. In Fig.6 (a), number six corner point is an error point, because there is a black noise point in that place, and to which traditional Harris corner detection is sensitive. However, the error corner point does not appear in Fig.6 (b). The experimental results indicate that multi-scale Harris corner detection has stronger resistance to noise ability.

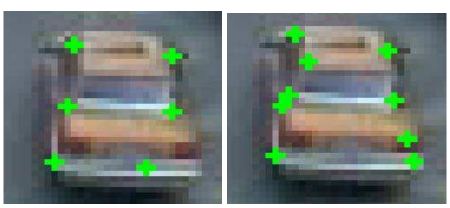
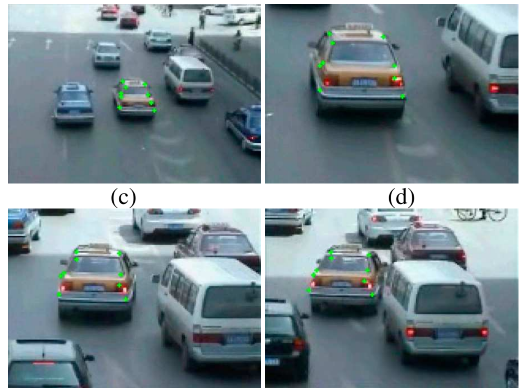

(a) (b)

Fig.6 Traditional Harris corner detection compared with multi-scale Harris corner detection


(a) (b)


(c) (d)

(e) (f)

Fig 7. Tracking right turning vehicle

In Fig.7 (a), (b), (c), (d), (e), the corner points are steady all the time when the car and background is moving and turning, and the camera is zooming in and out. In Fig.7 (f), when the cars are dense, the locations of all the corner points are still right.

Table1. Corner Coordinates and Error of Two Kinds of Corner Detection Algorithm

No.	Traditional Harris corner detection		Multi-scale Harris corner detection	
	Coord-inates	error of the location	Coord-inates	error of the location
1	86,33	2.18%	86,32	1.09%
2	101,31	1.35%	10029	0.96%
3	85,20	1.14%	85,21	0.10%
4	100,19	1.95%	101,19	0.97%
5	83,9	1.20%	83,9	1.20%
6	97,111	Error point	84,19	1.16%
7			105,8	0.95%
8			104,13	0.95%
9			88,27	1.09%

The proposed algorithm has some advantages, such as low computational complexity, short processing time and high real-time performance, compared with D. J. Fleet algorithm based on phase information and D. J. Heeger algorithm based on energy information. On the Pentium(R) Ⅳ 3.06GHz platform, 35 frames, the size of which is 320× 240 pixels can be processed in 1 sec. Furthermore, the algorithm can steadily track without complicated template update when the object is rotating and moving, and the camera is zooming in and out, compared with the tracking algorithm based on template matching.

5 CONCLUSION

Multi-resolution optical flow tracking algorithm based on wavelet pyramid is proposed by analysing the limitations of sparse optical flow based on LK algorithm. The algorithm decomposes D to some small displacements in the wavelet pyramid, and the small displacement meets the requirement of the LK algorithm. From the result of the experimentation, we can draw a conclusion that the tracking is steady and the feature corner points are accurately matched. With regard to the feature selection, multi-scale Harris corner detection based on wavelet is proposed. The result of the experimentation shows that the number of the corner points increases, and their distribution is more symmetrical. It provides the strong support to the optical flow tracking.

When the object is entirely occluded, all the corner points will be lost, and the tracking must fail. The potential method to solve this problem may be prediction and estimation algorithm. By prediction and estimation algorithm object is detected again in the possible region, and the tracking starts again.

ACKNOWLEDGMENT

This research was funded by International Grand cooperation project of Ministry of Science and Technology (No. 2003DF020009).

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