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A New Object Tracking Algorithm Based on the Fast Discrete Curvelet Transform

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Abstract

Tracking object from video sequences has become a very popular problem in the field of computer vision. Many algorithms have been proposed to solve this problem. Combined with the energy of curvelet coefficients and Kalman filter method, a new object tracking algorithm is proposed based on fast discrete curvelet transform. Firstly, this algorithm is initialized with the establishment of a moving object template and a number of undetermined objects are got with the search strategy. Then, feature vectors are constructed by energy of curvelet coefficients. Finally, the moving object is tracked in next frames using similarity function to match the feature vectors. Experimental results demonstrate the tracking accuracy and efficiency of the proposed algorithm under occlusions.

Keywords: *Object Tracking*; *Fast discrete curvelet transform; Kalman filter; Object template*

1. Introduction

Object tracking has widely application in many areas, such as intelligent video surveillance system, human robot interaction, security. The topic of tracking object in video has obtained extensive attention of researchers. Due to the problems in object tracking, such as noise, object conflict and object occlusion, the task of object tracking is a very large challenge. In order to solve these problems, many tracking algorithms have been proposed so far [1].

Fukunage and Hostetler [2] proposed the mean shift algorithm for data clustering. It is used for tracking a moving face by Bradski [3].More recently, mean-shift tracking algorithms have been applied in object tracking and proved to be robust to partial occlusions [4, 5]. Comaniciu demonstrated an object tracking method based on Kalman filter [6]. Kalman filter was used to estimate the state of an object in tracking by Emadedeen [7].

The key of object tracking is feature extraction and match. Wavelet transform as a new frequency transform method is a strong tool for detecting and analyzing singularities in signal. Wavelets are suitable for representing object both in space and frequency [8]. Therefore, most of object tracking algorithms are based on wavelets. Khare developed an algorithm for tracking objects in noisy video sequences [9] by using the well directional selectivity of dual-tree complex wavelet transform. The wavelet transform effectively reflects the singularity of points, but it achieves optimal approximation abortively in processing the singularity of lines. Ridgelet transform [10] was proposed to overcome the shortcomings of wavelet transform in processing high-dimensional images. In 2005, Xiao

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designed an object tracking system based on ridgelet transform, and proved that ridgelet was an alternative to wavelet transform in image description.

Ridgelet transform only provides a good representation for line singularities, and it is difficult to express the curve singularity. Thus, in 1999, Candes and Donoho proposed the first generation curvelet transform (FGCT), namely curvelet transform [11]. Curvelet transform combines the multi-scale of wavelet transform and the multidirectional of ridgelet transform, expressing the edge of the image efficiently. Nigam took full advantage of the characteristics of curvelet coefficients for tracking objects [12]. Later, Candes proposed a new framework of curvelet in 2002, called the second generation curvelet transform [13], which is also called fast discrete curvelet transform(FDCT). The new theoretical framework improves the speed of curvelet transform. After this, in 2005, they proposed two implementation methods based on fast discrete curvelet transform [14]. Compared with the original implementation methods, these implementation methods were simpler and faster, and greatly reduced the redundancy of traditional methods.

This paper presents a moving object tracking algorithm based on fast discrete curvelet transform and Kalman filter. This algorithm contains two steps: use of the energy of curvelet coefficients for feature vectors establishment and use of the metric similarity function for object match.

The rest of this paper is organized as follows: Section 2 describes basic concepts of curvelet transform. Section 3 illustrates an object tracking method based on curvelet transform. Section 4 deals with the theory of Kalman filter and the choice of parameters. Section 5 introduces the realization processes of the proposed method. Experimental results and conclusions are respectively given in Sections 6 and 7.

2. Curvelet Transform

Fast discrete curvelet transform is structurally different from the first generation curvelet transform. The first generation treats curve line as straight line through sub-band decomposition, and then uses ridgelet theory to analyze different sub-bands. Fast discrete curvelet transform and ridgelet theory are totally different. Ridgelet analysis is no longer part of the fast discrete curvelet transform. The only same point between the first generation and fast discrete curvelet is that they have the identical abstract mathematical sense, such as compact support and framework.

2.1. The First Generation Curvelet Transform

Donoho proposed the first generation curvelet transform. There are four steps in the implementation of the first generation curvelet transform. Firstly, an image is decomposed into different sub-bands, then windowing function applied on each small image obtained through sub-band decomposition. Each small image is renormalized to unit square. The last step is ridgelet analysis of each square. So, the first generation curvelet combines the anisotropism of ridgelet and the multi-scale of wavelet transform. The schematic diagram of the first generation curvelet is shown in Figure 1.

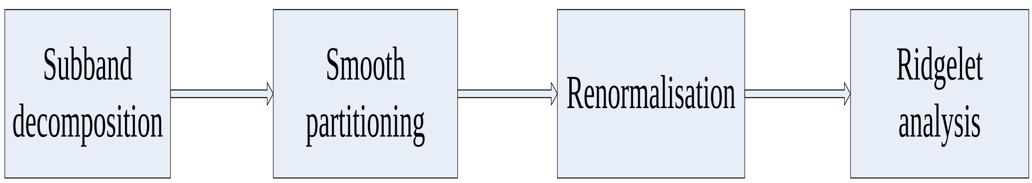


Figure 1.The Schematic Diagram of the First Generation Curvelet Transform

2.2. Fast Discrete Curvelet Transform

The function of curvelet transform is defined as:

$$c(j,l,k) = \left\langle f, \varphi_{j,l,k} \right\rangle \quad (1)$$

Among which, $\varphi_{j,l,k}$ is curvelet, j,l,k are the parameters of scale, direction and position respectively.

The input is $f[t_1,t_2],(0 \le t_1,t_2 < n)$ in Cartesian coordinate system, the discrete form of curvelet transform is:

$$c^D(j,l,k) = \sum_{0 \le t_1,t_2 < n} f[t_1,t_2]\overline{\varphi^D_{j.l.k}[t_1,t_2]} \quad (2)$$

There are two implementation methods of fast discrete curvelet transform. The first digital transformation is based on unequally-spaced fast Fourier transforms (USFFT) while the second is based on the wrapping of specially selected Fourier samples. The first implementation method in frequency domain is as follows:

1) The 2D FFT representation of function $f[t_1,t_2],(0 \le t_1,t_2 < n)$ is:

$$\hat{f}[n_1,n_2], -n/2 \le n_1,n_2 < n/2(j,l) \quad (3)$$

2) Resample each pair of scale and direction (j,l) of $\hat{f}[n_1,n_2]$ in frequency domain, the result is:

$$\hat{f}[n_1,n_2 - n_1 \tan\theta_l],(n_1,n_2) \in P_j \quad (4)$$

3) Multiplication of the interpolated function $\hat{f}$ with window function $\tilde{U}_j$,and the results is:

$$\hat{f}_{j,l}[n_1,n_2] = \hat{f}[n_1,n_2 - n_1 \tan\theta_l]\tilde{U}_j[n_1,n_2] \quad (5)$$

4) Transform function $\hat{f}_{j,l}$ by 2D IFFT. The discrete curvelet coefficients are defined as $c^D(j,l,k)$.

3. Object Tracking Method based on Curvelet Transform

In this algorithm, object tracking begins by selecting an object template in the first frame. A feature vector of the object template is constructed by using the coefficients in the curvelet domain. In next step, we establish feature vectors of undetermined objects, which is generated by search strategy. The final step is matching the object template and undetermined objects with the similarity function. Steps of this method are shown in Figure 2.

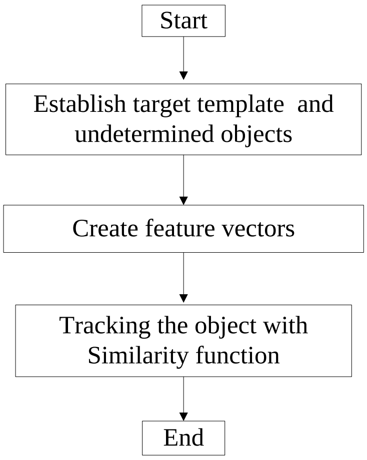


Figure 2. The Steps of Object Tracking Method based on Curvelet Transform

3.1. Feature Vector Establishment

In this step, the feature vectors of object template and undetermined objects are established by the energy of curvelet coefficients. The energy of curvelet coefficients is mainly concentrated in the low frequency sub-band after decomposed the image in curvelet domain. If we take use of the low-frequency coefficients to create feature vector, the amount of data is large and the tracking speed is very slow. Most of the high frequency coefficients include image edge information, so the energy of high frequency coefficients is more suitable for feature vectors establishment.

The tight frame property of curvelet permits us to divert attention to the coefficient domain.

$$\sum_{\mu} |< f, \gamma_{\mu} >|^2 = \| f \|^2_{L_2(R^2)} \qquad (6)$$

Thus magnitude and energy of curvelet coefficients remain approximately invariant by translating the object in different frames of video. The proposed tracking algorithm exploits this property.

The energy of curvelet coefficients can be defined as follows:

$$E = \sum_{(i,j)\in S} | curve - coef_{i,j} |^2 \qquad (7)$$

Where $curve\_coef_{i.j}$ is curvelet coefficient at $(i,j)^{th}$ point.

The feature vector is defined as follows:

$$E = [E_1 \, E_2 \, \cdots E_n]^T \qquad (8)$$

Where n is the scale of curvelet transform.

3.2. Similarity Function

The feature vector is obtained by curvelet coefficients, and similarity function can measure the similarity between object template and undetermined objects. $E = [E_1 \, E_2 \, \cdots E_n]^T$ is feature vector of object template. $E^{'} = [E_{i1}^{'} \, E_{i2}^{'} \, \cdots E_{in}^{'}]^T$ is feature vector of undetermined object. If the following formulas are satisfied, the corresponding location of feature vector M is the location of the moving object to track.

$$\Delta E_i = \sum_{j=1}^{n} | E_j - E_{ij}^{'} | \qquad (9)$$

$$M = \min(\Delta E_1 \, \Delta E_2 \cdots \Delta E_m) \quad (10)$$

Where M is the most similarity feature vector of object template.

3.2. Search Strategy

Assume that the search window is a rectangular block. Consider sixteen different undetermined objects at the various directions with distance of 1-2 pixels from the center of search window at current frame (Figure 3).

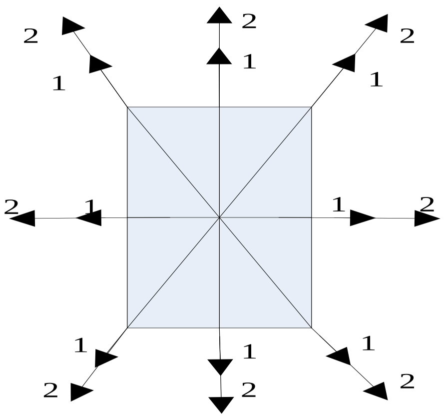


Figure 3. The Search Window

4. Kalman Filter

In curvelet transform method, we calculate the position of moving object. When the object is occluded, curvelet coefficients inaccurately express the edges of object and the position is not accurate. Kalman filter can effectively predict the optimal position when the object is occluded and get reliable tracking results.

Kalman filter is a minimum criterion based on the error covariance optimal estimation method. Kalman filtering algorithm can predict the probable location of object in the current frame according to the results of objects in the previous frames. After that we can search object location in the neighbor area. If there is an object existing in the search area, it will continue to process the next frame and update parameters. This method not only improves the precision of estimated value, but also takes into account the real-time of systems.

The state equation of the system is (11), and observation equation is (12).

State equation:

$$X_k = F \cdot X_{k-1} + W_k \quad (11)$$

Observation equation:

$$Z_k = H \cdot X_k + V_k \quad (12)$$

Where X_k is state vector of the system and Z_k is observation vector of the system. F is state transition matrix. H is observation matrix. W_k is dynamic noise corresponding to state vector, and V_k is measurement noise corresponding to observation vector. They are satisfied by:

$$p(w) \sim N(0,Q), \quad p(v) \sim N(0,R)$$

And Q_k and R_k are covariance matrixes of W_k and V_k respectively.

$X_k = [tic\_x, tic\_y, vx, vy, ax, ay]^T$ is state vector of the system, and $Z_k = [tic\_x, tic\_y]^T$ is observation vector of the system. tic_x, vx, ax are the position, velocity and acceleration of target in the x-axis, tic_y, vy, ay are the position, velocity and acceleration of target in the y-axis.

Prediction equation and the update equation are as follows:

Prediction equation 1:

$$X_k^{'} = F \cdot X_{k-1} \tag{13}$$

Prediction equation 2:

$$P_k^{'} = F \cdot P_{k-1} \cdot F^T + Q \tag{14}$$

Kalman-gain equation:

$$K_k = P_k^{'} \cdot H^T \cdot (H \cdot P_k^{'} \cdot H^T + R)^{-1} \tag{15}$$

Update equation 1:

$$X_k = X_k^{'} + K_k \cdot (Z_k - H \cdot X_k^{'}) \tag{16}$$

Update equation 2:

$$P_k = P_k^{'} - K_k \cdot H \cdot P_k^{'} \tag{17}$$

The values of state transition matrix F, measurement matrix H, process noise covariance matrix Q, measurement noise covariance matrix R list as follow:

$$F = \begin{bmatrix} 1 & 0 & T & 0 & T^2/2 & 0 \\ 0 & 1 & 0 & T & 0 & T^2/2 \\ 0 & 0 & 1 & 0 & T & 0 \\ 0 & 0 & 0 & 1 & 0 & T \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{18}$$

$$H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{19}$$

$$Q = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{20}$$

$$R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{21}$$

5. The Proposed Algorithm

This algorithm is described in Figure 4. Firstly, we select the moving object as object template in the first frame. Then, Kalman filter is used to estimate the position of object in the next frame. In the predicted area, we search the object with the feature vectors established by fast discrete curvelet coefficients. If searching success, the object is tracked. If searching fails, it means that the object is blocked by other objects, so the result of Kalman filter is the location of moving object.

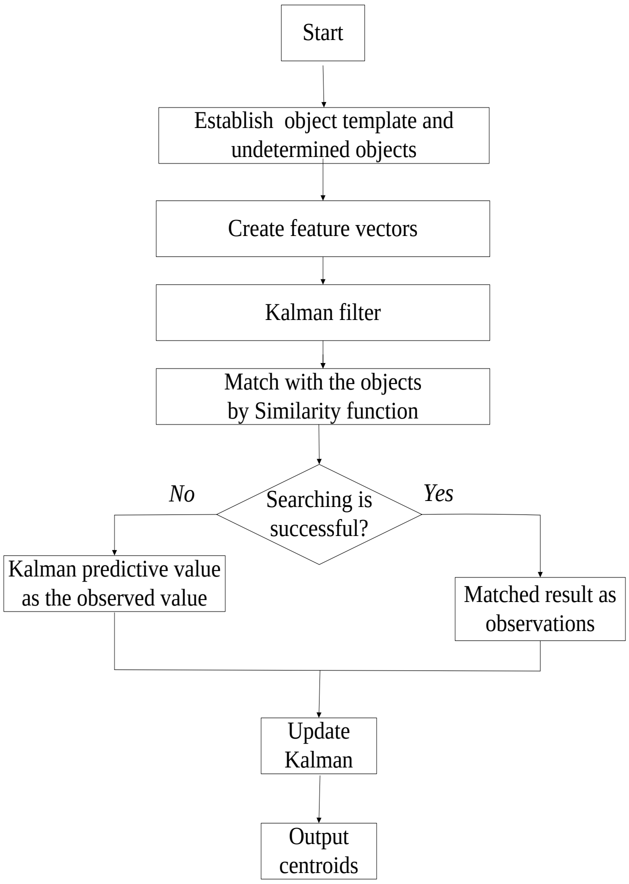


Figure 4. The Block Diagram of the Proposed Algorithm

6. Experimental Analysis

In this section, we show the experimental results of the proposed method. In case study 1, the first generation curvelet transform method and fast discrete curvelet transform method are respectively used to track objects. In case study 2, we have tested the proposed method in comparison to curvelet transform method and mean shift method. This test video contains totally 160 frames, size of frame are 432*240.

6.1. Case Study 1

The experimental results of curvelet transform method are shown in Table 1. In the experiment, the first generation curvelet coefficients and fast discrete curvelet coefficients are respectively used to establish the feature vectors. Experimental environment: the Core 2 Duo processor, 2.5G memory and matlab7.0.The experiment proves fast discrete curvelet transform method not only has a higher speed than the first generation curvelet transform method, but also has a much smaller number of computations than it.

Table 1.The Time of Moving Objects Tracking

Tacking method	Tracking time by per frame	Total Time
Object tracking method based on first generation curvelet	139.7s	22352s
Object tracking method based on fast discrete curvelet	1.95s	312s

6.2. Case Study 2

In this case, curvelet transform method, mean shift method and the proposed method are respectively applied on the video. The results are shown in Figure 5. The x and y direction actual centroids and centroids computed through curvelet transform method, mean shift method and the proposed method are shown in Figure 6(a) and (b).

(a) (b) (c)

Frame NO 10

(a) (b) (c)

Frame NO 30

(a) (b) (c)

Frame NO 60

(a) (b) (c)

Frame NO 90

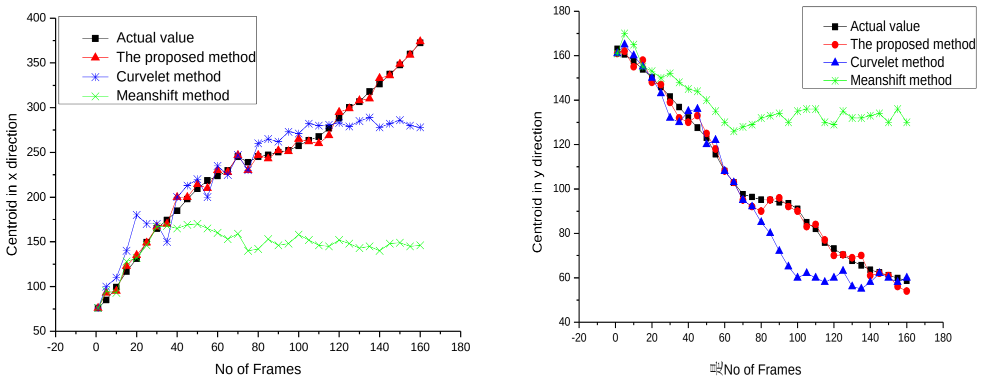
(a) (b) (c)

Frame NO 120

(a) (b) (c)

Frame NO 160

Figure 5. Tracking of People in Frames. (a) Curvelet Transform Method, (b)Mean Shift Method,(c) the Proposed Method



(a) (b)

Figure 6. (a) x Direction Centroids of Moving Object (b) y Direction Centroids of Moving Object

The simulation results in Figure 5 and the centroids of moving object in Figure 6 are all shown that mean shift algorithm will cause the object loss if the object overlaps other objects. When a large area of object is covered, the tracking method based on curvelet transform will be fail. This proposed algorithm takes advantage of the predictive ability of Kalman filter and the accuracy of curvelet coefficients energy in description edges. This method can track objects under occlusion.

7. Conclusion

In this paper, a new method based on fast discrete curvelet transform has been proposed for object tracking. Curvelet transform derives from wavelet transform, and it overcomes the shortcomings of wavelet transform in the expression of image edges. The anisotropic characteristic of curvelet transform provides an ideal representation of the object edges. The proposed method establishes a feature vector with the energy of fast discrete curvelet coefficient for searching the moving object, and combines with Kalman filter for reducing the object searching range and forecasting the location of object when occlusion occurs. In the part of experiment, fast discrete curvelet transform method performs very well through comparing with the first generation curvelet transform method in terms of speed. On the comparison of three different tracking methods show that the proposed method can accurately track the object when the object occlusion occurs.

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