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Research of ASM Object Tracking Method Combining Kalman Estimation

Liguo Zhang, Mei Jin*

Measurement Technology and Instrumentation Key lab of Hebei Province, Yanshan University, Qinhuangdao, China.

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ABSTRACT

ASM is a statistical model applied to match contours of non-rigid object. Although ASM is good at non-rigid object tracking, the result depends on the prior gray level model. When there is a great deformation in the process of target tracking, the gray information changes dynamically. The actual contour may much different from the initial contour and the result is likely to converge to an error contour. Kalman filter is adopted to track the current frame for the prediction and acts as the initial state of the ASM, and then applies the ASM to correct the contour of the object. Experimental results show that the method proposed in this paper allows the model to converge to the target contour quickly and accurately. It has good stability and robustness.

1. Introduction

In the computer visual system, the target recognition and tracking[1-3] is equivalent to the feature-based matching in an image or between continuous image frames. We have a variety of options to describe the characteristics of the objects, such as shape, speed, position, color, and texture. Reasonable selection of target feature is an important factor to achieve high quality identification and tracking. The shape, as one of the essential characteristics of the objects, basically does not change in the most cases. We can quickly identify the various targets in the different scenes, or even make the correct classification of the targets only on the basis of the edge contour. Therefore, we select edge contour as a target characterization. To the contour tracking, the first problem to be solved is the contour extraction which on the one hand separates the target from the background to achieve detection, on the other hand provides the data source to achieve the object identifying and tracking. On the basis of contour extraction, target tracking method based on contour feature centers on snake model. Fu et al put forward occlusion adaptive snake tracking method[4]. The target contour is divided into several regions based on color, curvature and movement characteristics. The divided regions are divided into the target area and the background area. It estimates the positions of these two areas in each frame and only selects the un-occluded portion as the integral part of the contour. Peterfreund proposed the optical flow and the edge of the contour as Kalman Snake of system observation[5].This approach improves the robustness of the contour tracking in the case of occlusion and confusion. Szeliski and Terzopoulos proposed a contour tracking method combining the Kalman filter[6,7] and Snake model[8,9]. This paper studies the target tracking method based on ASM, which has the superiority over Snake model in robustness. Aiming at the problem of the error contour convergence due to the initial positioning of the model, which may happen during the ASM tracking process, this paper proposes the use of Kalman filter to track the contour of the current frame, and then predicts the state in the next frame. It makes the result as the initial state of the ASM. At last, it applies the ASM to correct the object contour.

2. ASM method

2.1 Introduction to ASM method

Active shape model is a statistical model applied to the non-rigid contour matching[10-14]. It has a tracking function itself. Traditional target tracking methods, such as particle filter and Meanshift algorithm, are able to accurately position the target area. However, when we are tracking non-rigid target, different degree of deformation may occur in the process of movement. Just by using the regional information, it can not meet the accurate extraction of the target characteristics. ASM model obtains global shape model and local texture model by statistical analysis of the samples in the training set[15]. Shape model searches target contour relying on texture model, and adjusts its shape to be consistent with the target contour constantly.

2.2 Target tracking based on ASM method

Simply speaking, target tracking searches the accurate target

* Corresponding author.
E-mail addresses: meijin297@126.com (M.Jin)

position in the continuous image sequence for determining the target trajectory. A common tracking idea is to establish a certain characteristics of the target model. After that we search each image frameto find the exact location of the target via the feature model matching. Feature model selection has been carried out in the introduction in detail and we select edge contour as a moving target characterization. This paper researches moving target tracking based on ASM method. This method uses shape model matching object contour in a continuous sequence of images for the tracking purposes. Generally speaking, ASM method can be carried out in the following order:

(1) Give the initial contour of the n-th frame image to be treated;

(2) Reasonable adjustments to the model to make the model consistent with the target contour; Start the iterative process;

(3) The contour result of the n-th frame is set to the initial contour of the n+1 frame;

(4) Repeat the above operations until all the images are processed.

According to the description above, ASM is a good tracking method for flexible objects. However, since the reliability of the matching results depend on the prior gray model, when the the gray information dynamic changes, the effect based on ASM is poor in target tracking. It is prone to large deformation in the tracking process, especially for flexible object. When the contour result of the n-th frame is as the n+1 frame's initial contour, if object occur large changes between the two frames, the actual contour of the n+1 frame will be very different from the initial contour set. ASM is likely to converge to a wrong contour.

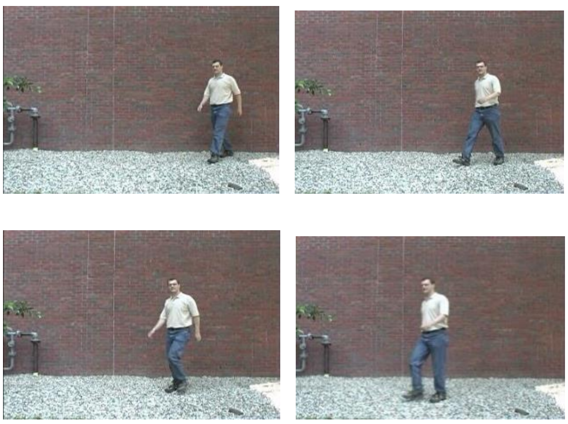


Fig.1. Screen-shots of the selected video

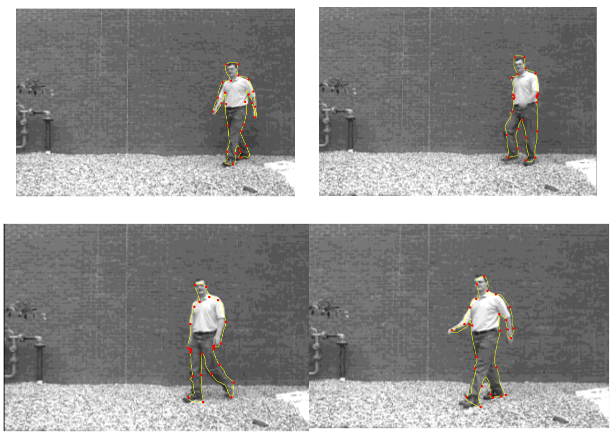


Fig.2. Tracking shot of the traditional ASM method

This paper makes a simulation experiment of human motion using the traditional methods of ASM tracking to describe the problem. Fig.1 is the screen-shots of the video for the experiment.

The simulation collects 27 landmarks for each sample in the training set. After the repeated experiments, five points distribute evenly among adjacent landmarks, which can get the clear result. The shape parameters of the shape model are limited to $3\sqrt{\lambda_i}$ (λ_i is eigen value). Choose the length of the gray-scale model as 8, and select the research length as 6. To make the experiment results clear, the experiment marks the contour and the main landmark points together. Fig.2 is the result of the simulation experiment. Simulation Results.

Analyzing the simulation results, then we can clearly observe that during the process of target motion, the contour of previous state of motion tracking results affects the convergence results of the current motion state. The10th screen-shots convergence result is affected by the previous state. The center of gravity moves up. The convergence result of the 23th moves down. The 36th convergence result has a greater deviation because of the infuence of the previous cumulative errors. An important factor to affect the ASM method of matching effect which can be seen is the initial positioning of the model. If the initial position is close to the target position, the model can converge in a fewer number of iterations to the target contour. Conversely, if the initial location is far away from the target, the convergence speed is slow or even it can not converge correctly. When tracking a moving target, even between two adjacent images targets, it may have a larger displacement. So, when applying ASM method, we need to estimate the approximate location of the target for the initial positioning of the model. Therefore, in order to avoid possible errors convergence and accelerate the convergence speed of the ASM, this paper uses the kalman filter[16-18] to track the current frame for the prediction and acts as the initial state of the ASM, and then applies the ASM to correct the contour of the object.

3. Motion estimation based on Kalman filter

Kalman filter is an optimal estimation which is based on the previous state of the system to estimate the next state[19-20]. The estimation has the stable, unbiased and optimal advantages. Generally speaking, in a system containing noise, x_k represents the state of the system at the moment t_k. A feature vector is represented by z_k in t_k moment observed. We can make an estimation of x_k based on z_k. If we also know that how x_k changes, we will be able to make a prediction of x_{k+1}. The idea of Kalman filter is the prediction feedback mechanism.

The equation of the state of system is:

$$x_k = Ax_{k-1} + w_{k-1} \tag{1}$$

For the convenience of calculation, this simulation assumes that there is no outside input. The system matrix B array is 0.

The observation equation is:

$$z_k = Hx_k + v_k \tag{2}$$

The goal of the Kalman filter is that we've known the system transfer matrix A, the observation matrix H, the error covariance matrix of the process excitation noise Q and the error covariance matrix of the process observation noise R, x_k can be recovered from the observed z_k.

The process of Kalman filter is as follows:

The first step is to forecast:

$$\hat{x}_k^- = A\hat{x}_{k-1} \tag{3}$$

$$P_k^- = AP_{k-}A^T + Q \tag{4}$$

The system transfer matrix A is

$$A = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

where Δt is time interval between adjacent two frames.

The second step is to correct based on the observed results

$$K_k = P_k^- H^T \left(HP_k^- H^T + R\right)^{-1} \tag{6}$$

$$\hat{x}_k = \hat{x}_k^- + K_k\left(z_k - H\hat{x}_k^-\right) \tag{7}$$

$$P_k = \left(I - K_k H\right)P_k^- \tag{8}$$

Because the target position can only be observed in the image and the target speed can not be observed directly, the observation matrix H is as follows:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{9}$$

Assuming that w_k, v_k are noise components independent of each other and have zero mean, so Q and R are respectively follows:

$$R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{10}$$

$$Q = \begin{bmatrix} 0.1 & 0 & 0 & 0 \\ 0 & 0.1 & 0 & 0 \\ 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 10 \end{bmatrix} \tag{11}$$

Kalman filter uses recursive estimation method. If the initial state of filter equation and error covariation matrix of the priori estimate are given, the estimate value of system state can be obtained by the current measured value. The initial value of error covariation matrix of the priori estimate is:

$$P = \begin{bmatrix} 0.01 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0.01 \end{bmatrix} \tag{12}$$

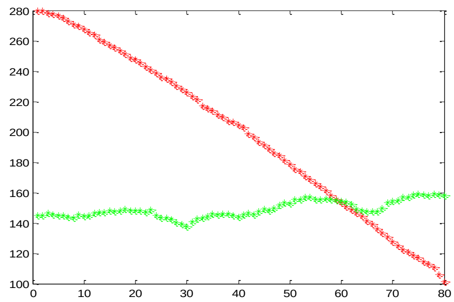
After continuous cycle of these two steps, we can get the estimation of various moments of the system.

As can be seen from the formulas, the elements in the covariance matrix of observation noise are larger, the Kalman gain is smaller. Therefore the smaller the amount of correction is predicted. This is because the greater the elements in the covariance matrix of observation noise are, the smaller the credibility of observed value is. Finally estimated value is closer to the predicted value.

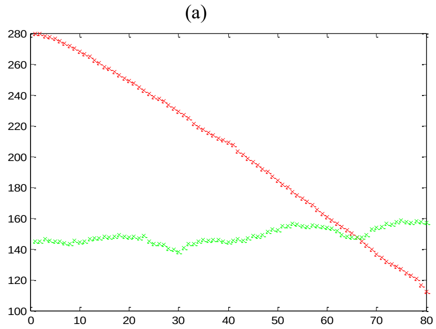
Use Kalman filter for motion tracking. The state vector is the position and velocity of an object, and each of which have the two directions. So the state vector is four-dimensional. The state transition matrix is the relationship of the location and the speed between the current and the last moment. As the adjacent inter-frame time is very short, we assume that the speed is constant. The new position is equal to the previous time position plus the speed multiplied by the sampling period. Then we can get the state transition matrix. The components of the positions in the two directions of the state vector are removed from the observation matrix, because the speed is not observed. The process noise is caused by the moving object acceleration. Observation noise is caused by the inconsistent of foregoing moving objects and regional connectivity.

This experiment uses the video mentioned above. To illustrate the prediction function of the Kalman filter, we extract the outer contour with no requirements for the rest of the feature information. The tracking process is relatively simple. For the convenience, the experiment assumes that the motion of an object detected has no outside input. The process noise and observation noise obey Gaussian distribution. Figure 3 is the simulation result of Kalman filter motion estimation. Four images are intercepted in the course of motion.

Fig.3. Kalman filtering motion estimation .



(a)



(b)

Fig.4. Prediction point and the center of the trajectory

From the experiment results, tracking results are quite satisfied, which is in line with the actual trajectory of the moving target. Fig.4 (a) is a prediction of the trajectory of the center point. Fig.4(b) is the estimation trajectory of the center point. Abscissa represents the number of frames. Red trajectory lines in Fig.4 (a) and (b) respectively represent the coordinates of the prediction points and the estimated points in the X-axis direction. The green trace lines in Fig.4 (a) and (b) represent the prediction points and the estimated points of the coordinate in the Y-axis direction respectively. It can be seen that the predicted points and the estimated poinst are very similar.

In order to show the effects of the estimation of Kalman filter more intuitively, the experiment puts true trajectory, the predicted trajectory and the estimated trajectory of the moving target on the same coordinate system, as shown in Figure 5.

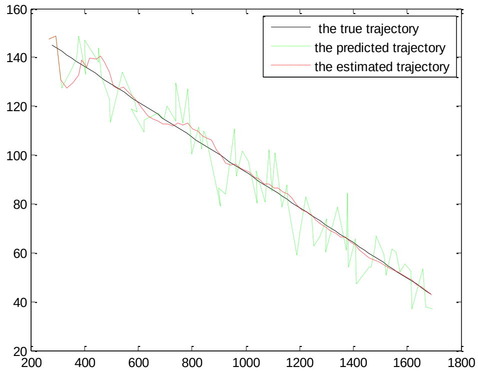
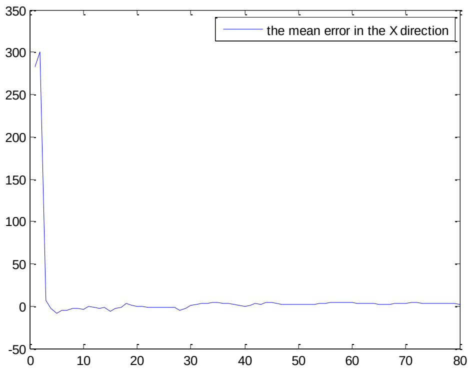
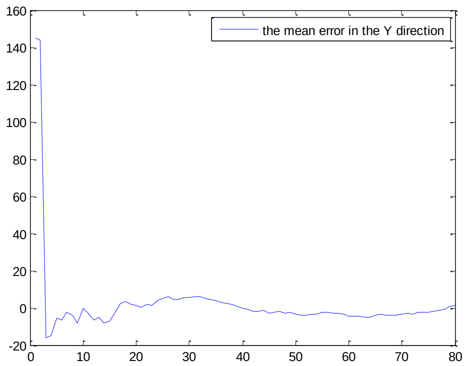


Fig.5. Three trajectories comparison

Let the true trajectory subtract the estimated trajectory, and then obtain the error curves in the x-direction and y-direction respectively, shown in Fig.6 (a) and (b).



(a)



(b)

Fig.6. The error curves in the x-direction and y-direction

4. Target tracking combined ASM and kalman filter

Use the same video, training samples and ASM model as in the subsection 2. Simulation experiment in this section uses a combination of the Kalman filter and ASM method to track the target. The results are shown in Fig.7, which show that when the target motion, shape and posture change, Kalman filter is able to effectively detect the target and narrow the distance between the initial position of the model and the target position. This paper takes advantage of the inter-frame similarity characteristics and makes the previous convergence result as the initial shape of the current frame, which allows the model to converge to the target contour quickly and accurately. The combination of the Kalman filter and ASM method has good stability and robustness.

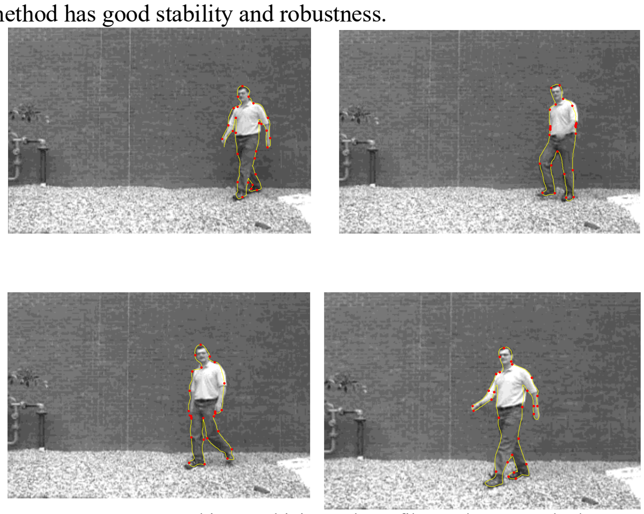


Fig.7. Target tracking combining Kalman filter and ASM method

5. Conclusion

This paper describes a moving target tracking method based on ASM combining the Kalman filter estimation. Aiming at the problem that the ASM tracking method may have the wrong convergence, this paper uses Kalman filter to track the contour of the current frame, predicts the state of the next frame, and uses this as the initial state of the ASM. Then it applies the ASM to correct the contour of the object. Experiment results show that the use of Kalman filtering algorithm greatly reduces the distance between the initial shape of the actual position and the target position. Compared with traditional methods, the method combining Kalman filtering and ASM algorithm has better robustness and accuracy.

Acknowledgements

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Liguo Zhang received his doctor degree in instrument science and technology from Yanshan University, Qinhuangdao, China, in 2010. He is currently an associate Professor of the Institute of Electrical Engineering, Yanshan University. His current research interests include image processing and machine vision.
Email: zlgtime@163.com

Mei Jin received her doctor degree in Control theory and control engineering from Yanshan University, Qinhuangdao, China, in 2010. An associate Professor of the Institute of Electrical Engineering, Yanshan University. His current research interests include image processing and control of robots.
Email: meijin297@126.com