Application of Particle Filter in Video Moving Target Tracking

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Abstract: Aiming at solving the problem of large tracking error in the tracking process of video moving targets with the unscented Kalman filtering method, a particle filter algorithm is proposed to track video moving targets to improve the tracking effect. Particle filtering is the minimum variance estimation of the system state through the posterior probability distribution. The applications of particle filtering and unscented Kalman filtering in tracking video moving target are compared by using Matlab simulation software. The results show that the particle filter has higher accuracy and better tracking performance than the unscented Kalman filter in tracking video moving target.

1. Introduction

With the rapid development of science and technology, video moving target tracking technology has become a research hotspot in the field of computer vision in recent years [1]. It is based on a priori information of the target's apparent characteristics and the target state motion model and obtains the position and range of the target through inference. However, there are still some difficult problems, such as the problem that the Unscented Kalman Filter (UKF) filter performance will decline in non-Gaussian systems [2], [3]. However, Particle Filter (PF) can effectively solve the non-linear and non-Gaussian problems [1], [4]. This is because the PF gets rid of the constraint that Gaussian distribution must be satisfied when solving nonlinear filtering problems, and it can express a broader distribution than the Gaussian model, and also has a stronger modeling ability for the nonlinear characteristics of variable parameters [5]. Therefore, PF is used to track and estimate targets in the paper. The idea of PF is based on the Monte Carlo method. The core is to express the distribution of random state particles extracted from the posterior probability.

2. Principle of particle filtering

Video moving target tracking problems can generally be described by state space models, assuming that the state equation and observation equation are composed as follows:

\[ x_k = f(x_{k-1}) + w_{k-1} \]  \hspace{1cm} (1)

\[ z_k = h(x_k) + v_k \]  \hspace{1cm} (2)

Among them, \( x_k \) is the target state at time \( k \), \( z_k \) is the target measurement at time \( k \), \( f(\cdot) \) is a non-linear
state transition function, \( h(\cdot) \) is a non-linear state observation function, \( w_{k-1} \) is independent and identically distributed state noise, and \( v_{k} \) is independent and identically distributed observation noise.

Based on the importance sampling principle, the weights of the particles can be obtained. Since \( p(x_{0:k} \mid z_{1:k}) \) is the posterior probability density function finally obtained, the particles cannot be directly sampled. Therefore, indirect methods are usually used to achieve particle importance sampling. Assuming particles can be sampled from the importance density function \( q(x_{0:k} \mid z_{1:k}) \), then \( p(x_{0:k} \mid z_{1:k}) \) can be approximated as

\[
p(x_{0:k} \mid z_{1:k}) \approx \sum_{j} w^{(j)}_{k} \delta(x_{0:k} - x^{(j)}_{0:k})
\]  

Among them, \( \delta(\cdot) \) is the Dirac delta function,

\[
w^{(j)}_{k} \propto \frac{p(x^{(j)}_{0:k} \mid z_{1:k})}{q(x^{(j)}_{0:k} \mid z_{1:k})}
\]  

The target state \( x_{k} \) at time \( k \) depends only on the target state \( x_{k-1} \) at time \( k-1 \) and the measurement \( z_{k} \) at time \( k \), then

\[
p(x_{0:k} \mid z_{1:k}) = \frac{p(z_{k} \mid x_{k})}{p(z_{k} \mid x_{k-1})} \frac{p(x_{0:k-1} \mid z_{1:k-1})}{p(x_{0:k-1} \mid z_{1:k-1})} \propto p(z_{k} \mid x_{k}) \frac{p(x_{0:k-1} \mid z_{1:k-1})}{p(x_{0:k-1} \mid z_{1:k-1})}
\]  

\[
q(x_{0:k} \mid z_{1:k}) = q(x_{k} \mid x_{k-1}, z_{k})q(x_{0:k-1} \mid z_{1:k-1})
\]  

Equation (4) can be written as

\[
w^{(j)}_{k} \propto \frac{p(z_{k} \mid x^{(j)}_{k})}{q(x^{(j)}_{k} \mid x^{(j)}_{k-1}, z_{k})} \frac{p(x^{(j)}_{0:k-1} \mid z_{1:k-1})}{q(x^{(j)}_{0:k-1} \mid z_{1:k-1})} = w^{(j)}_{k-1} \frac{p(z_{k} \mid x^{(j)}_{k})}{q(x^{(j)}_{k} \mid x^{(j)}_{k-1}, z_{k})}
\]  

In general, the prior probability density function is selected as the importance density function, which is

\[
q(x_{k} \mid x^{(j)}_{k-1}, z_{1:k}) = p(x_{k} \mid x^{(j)}_{k-1})
\]  

Substituting equation (8) into equation (7), we can get

\[
w^{(j)}_{k} \propto w^{(j)}_{k-1} p(z_{k} \mid x^{(j)}_{k})
\]  

Integrate \( x_{0:k-1} \) by equation (3), the approximate solution of the state posterior probability density function \( p(x_{k} \mid z_{1:k}) \) concerning particles can be obtained:

\[
p(x_{k} \mid z_{1:k}) \approx \sum_{j} w^{(j)}_{k} \delta(x_{k} - x^{(j)}_{k})
\]  

The weight of the particles can be obtained by formula (9), and when the number of particles \( N \to \infty \), equation (10) approaches the true state posterior probability density function \( p(x_{k} \mid z_{1:k}) \) 


After obtaining the posterior probability density update particle set \( p(x_k \mid z_{1:k}) \), the generally used state estimation method is Expected a posterior (EAP) estimation, that is, the weighted average of all particles is used as the estimated value

\[
x_k = \frac{1}{N} \sum_{i=1}^{N} w_k^{(i)} x_k^{(i)}
\]

(11)

The advantage of expecting posterior estimation is that it can satisfy the mean square error minimization.

3. Design of PF Algorithm in Video Moving Target Tracking

Sequential importance sampling (SIS) PF has a particle degradation phenomenon. To solve this problem, adding the resampling step based on SIS PF to obtain the sampling importance Sampling (Sampling Importance Resampling, SIR) particle filtering. SIR Sampling PF is the most commonly used particle filtering, and it is also the filtering method used in the paper for video target tracking.

Experimental background: In the video sequence, the small ball does a free-fall movement, bounces after touching the ground, and reciprocates until the small ball stops. The design of the algorithm is presented as follows:

1) Particle initialization: Sampling the initial particle set \( \{ (x, y)^{(i)}_0, N^{-1} \}_{i=1}^{\gamma} \) and \( p(x, y)_0 \), setting the time \( k = 1 \).

2) Particle prediction: Sampling particles \( (x, y)^{(i)}_k \) \( \sim \) \( p((x, y)_k \mid (x, y)^{(i)}_{k-1}) \), \( i = 1, 2, \ldots N \).

3) Update: Calculate the corresponding weight \( w(x, y)^{(i)}_k = p(z_k \mid (x, y)^{(i)}_k) \) of the particles, \( i = 1, 2, \ldots N \), and the weights are normalized \( \tilde{w}(x, y)^{(i)}_k = w(x, y)^{(i)}_k / \sum_{i=1}^{N} w(x, y)^{(i)}_k \).

4) Particle resampling: \( \{ (x, y)^{(i)}_{k-1}, N^{-1} \}_{i=1}^{\gamma} \) \( \sim \) \( \text{RESAMPLE} \{ (x, y)^{(i)}_k, \tilde{w}(x, y)^{(i)}_k \}_{i=1}^{\gamma} \} \).

5) State estimation: \( (x, y)_k = \frac{1}{N} \sum_{i=1}^{N} (x, y)^{(i)}_k \), to update \( k = k + 1 \), go to step.

4. Simulation analysis

It can be seen from Fig. 1 that between 0 and 60 frames in the X-axis direction, the tracking errors of the UKF and PF are small. Fig. 2 shows that between 0 and 60 frames in the y-axis direction, the UKF error is large, but the PF error tends to zero. Therefore, compared with the UKF algorithm, the tracking of the PF algorithm is closer to the actual trajectory map and the tracking effect is better.

In addition, by observing the movement of the small ball in the video, it can be known that the small ball does a free-fall movement, and constantly pat the table during the falling process until it finally stops. Fig. 3 is the tracking effect diagram of 10th, 20th, 30th, 40th, 50th and 60th frames. The yellow box is the PF tracking result, the blue box is the UKF tracking result, and the green box is the target ball, that is, the real motion state. From the simulation results, the UKF has a larger tracking error at the start, then the tracking error become smaller and smaller. However, the tracking error of the PF is almost zero, the PF nearly on the target at all the frames. Therefore, it can be concluded that the PF method always has better tracking performance during the ball’s free-falling motion compared with the UKF method, though the ball collides with the ground during this period.
Figure 1. Track results of X-axis.

Figure 2. Track results of Y-axis.

Figure 3. Comparisons of tracking effect diagram of 10th, 20th, 30th, 40th, 50th and 60th frames.

To evaluate the performance of the algorithm in detail, its statistical characteristics include mean absolute deviation, standard deviation of the estimated error, and correlation coefficient (CC) are compared.
The comparison results of the statistical characteristics of the two methods are shown in Table 1. It can be known from Table 1 that the average absolute deviation and the standard deviation of the estimation error of the PF algorithm are much smaller than those of the UKF algorithm, which indicates that the estimation error of the PF algorithm is smaller than that of the UKF and the estimation accuracy is higher. The correlation coefficient of the PF algorithm is closer to 1 than that of the UKF, which indicates that the tracking performance of the PF is better.

| The algorithms | $E[|e|]$ | $\sigma_e$ | CC       |
|----------------|---------|-----------|----------|
| UKF            | 1.1039726 | 3.7524438 | 0.9957059 |
| PF             | 0.9070596 | 1.1849872 | 0.9995688 |

5. Conclusion

The results show that the tracking effect of the two methods on the x-axis is not much different. During the tracking of a free fall movement of the ball, along the y-axis direction, when the ball hits the ground and bounces, especially when it first hits the ground, the unscented Kalman filter method cannot effectively track the ball. There is a relatively large error in tracking, but as the subsequent ball contacts the ground again, the error gradually decreases and the tracking effect gradually improves. However, it can be seen from the particle filter tracking effect diagram and the results of the statistical characteristics that the particle filter method can accurately track the ball. It almost coincides with the real ball movement. Therefore, the tracking effect of the particle filter method is better than that of the unscented Kalman filter.

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References

[1] Feng Liu, Shibin Xuan, Xiangpin Liu 2015 *Data Acquisition and Processing* 30 2 pp 452-463
[2] Xiaoping Huang, Yan Wang 2015 *Electronic Industry Press*, 2015.
[3] Longfei Ren, Guodong Liu 2012 *Journal of Jiangnan University (Natural Science Edition)* 11 6 pp 670-673.
[4] Haohai Fu, Hongchang Ke 2016 *Journal of Changchun Institute of Technology (Natural Science Edition)* 17 04 pp 85-88.
[5] Jin Tang. 2017 *Computer Knowledge and Technology* 13 (10): pp 149-150, 153.