IOP Conference Series: Materials Science and Engineering

PAPER • OPEN ACCESS

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To cite this article: HaiYan Chen *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **563** 042016

IOP Conf. Series: Materials Science and Engineering **563** (2019) 042016 doi:10.1088/1757-899X/563/4/042016

Abrupt motion tracking of Ochotona curzoniae via improved motion model based on particle filter

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Abstract. The movement of Ochotona curzoniae is random, unpredictable, and often accompany by abrupt motion, Ochotona curzoniae has protective coloration, and possesses the characteristic of having low contrast with its typical background. Particle filter algorithm has been widely used to solve tracking problems, they can solve nonlinear and non-Gaussian problems. The motion model of the particle filter tracking algorithm ignores the acceleration factor, the observation values of position could not represent the future position. Due to this problem, this paper introduces acceleration variance of the "current" statistical model to motion model. In addition, this study fuse color feature with gradient feature as an observation model to overcome interference factors like a complex background, and low contrast. The experimental results show that the improved motion model and observation model has a better performance for abrupt motion, and could accurately track Ochotona curzoniae.

1. Introduction

Ochotona curzoniae is an endemic species and a key species in the Qinghai-Tibet Plateau. Ochotona curzoniae is a rodent that causes great damages to grasslands[1], therefore research on motion tracking is a significant project. Target tracking is of great significance to the field of computer vision[2], and it can play an important role in various applications. Ochotona curzoniae run in unpredictable and random patterns, and often undergo mutations when they move smoothly. In addition, they possess the characteristics of having a low contrast, inhomogeneity of the object, diversity, and mutability. All these factors increase the difficulty in tracking Ochotona curzoniae. Abrupt motions, such as uncertain motion, camera switching, fast motion and low frame rate video, are common in real-world scenarios[3]. Kwon et al. presented a Wang-Landau Monte Carlo sampling based tracking method(AWLMC)[4] to deal with abrupt motion, and this method was suitable for global mutations. Su et al. proposed an improved visual saliency model and integrated it into a particle filter algorithm[5]. Although this method was robust in dealing with some types of abrupt motion, it was not suitable for Ochotona curzoniae tracking, because the target was not obvious. Wang et al. proposed an efficient algorithm that was a feature-driven (FD) motion model based on features from accelerated segment test (FAST)[6], however this method needed to obtain FAST features from the target, and it was difficult to obtain representative FAST features from Ochaotona curzoniae. Zhang et al. proposed an abrupt motion tracking method based on SIFT flow[7], which used SIFT flow characteristics to match the optimal target position.

In this study, for handling the abrupt motion of Ochotona curzoniae, we propose an improved motion model that introduces the acceleration variance of "current" statistical model, according to the relationship of acceleration variance $\sigma_a^2(k)$ with the prediction $\hat{x}(k)$ and observation z_k [8]. Since no

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single feature can be robust to deal with complex environmental conditions[9], fuse color feature to gradient feature as the observation model.

2. Particle filter algorithm

The motion model of the particle filter algorithm is generally an elliptical model, which can reduce extraneous information interferences in the background.

The target states can be expressed by a states vector, as follows:

$$s = [x, v_x, y, v_y, v_a, v_b, \theta]^T \tag{1}$$

where, x and y are center coordinates of the predictive target, v_x and v_y are change rates of the center coordinates, and θ is the inclination angle of the ellipse. Using the states equation to describe the motions of the target:

$$s_{k+1} = \Phi s_k + \omega_k \tag{2}$$

where, ω_k is zero-mean high dimensional Gaussian noise, and Φ is a states transition matrix.

3. Improved motion model

Due to the particle filter algorithm only considers position information and velocity information, while ignoring acceleration information, it has an inaccurate estimation of fast motion. In this study, we introduce acceleration variance based on the elliptical model. According to the relationship of acceleration variance with the prediction and observation, the relation equation is defined as follows:

$$\sigma_a^2(k) = \frac{2}{T^2} | \hat{x}(k) - z(k) | \tag{3}$$

where, $\hat{x}_k$ is prediction value of location, z_k is observation value of location, T is sampling period. The prediction of target motions in two - dimensional space is calculated by equation(4):

$$X_k = X_{k-1} + V_{k-1}T + 1/2\sigma_a^2(k-1)T^2 \tag{4}$$

where, $\sigma_a^2(k-1)$ is the variance of the k-1 frame, calculated by (5) and X_k can be written as (6):

$$\sigma_a^2(k-1) = \frac{4-\pi}{\pi}(a_{\max} - \hat{a}(k-1|k-2))^2 \tag{5}$$

$$X_k = [x, v_x, a_x, y, v_y, a_y, v_a, v_b, \theta]^T \tag{6}$$

The states equation can be written as (7):

$$X_k = \Phi_{k-1} X_{k-1} + \omega_{k-1} \tag{7}$$

The states transition matrix in this paper can be given by (8):

$$\Phi_k = \begin{bmatrix} 1 & 1 & A & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & B & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & A & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & B & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{8}$$

where, A and B are defined as follows:

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$$A = 1/2\sigma_a^2(k)T^2 \tag{9}$$
$$B = \sigma_a^2(k)T \tag{10}$$

4. Observation model

According to the tracking results, a low contrast and a complex background could interfere with the tracking box. In this study, the observation model is concerned with two kinds of features: the color feature and the gradient feature. The gradient feature can obtain spatial information from local shape information of the target, which is robust to illumination change and local deformation. The gradient feature needs to calculate the gradient amplitude value $G(x,y)$ and orientation $\theta(x,y)$ of each pixel $I(x,y)$, the expressions are defined as follows:

$$dy = I(x+1,y) - I(x-1,y) \tag{11}$$
$$dx = I(x,y+1) - I(x,y-1) \tag{12}$$
$$G(x,y) = \sqrt{dx^2 + dy^2} \tag{13}$$
$$\theta(x,y) = \arctan(\frac{dx}{dy}) \tag{14}$$

where, dx and dy are the difference of the pixel values.

The color feature has the characteristics of low sensitivity to scale change and rotation of the target. To reduce the impact of illumination, the RGB color space is changed to HSV color space. In this paper, adopt Bhattacharyya similarity measurement method, which require likelihood distribution of target $q(x_0)$ and candidate target $p(x)$:

$$q(x_0) = C\sum_{i=1}^{N} k(\left\|\frac{x_0 - x_i}{h}\right\|^2)\delta[b(x_i) - \mu]_{i=1}^{N} \tag{15}$$
$$p(x) = C\sum_{i=1}^{N} k(\left\|\frac{x - x_i}{h}\right\|^2)\delta[b(x_i) - \mu]_{i=1}^{N} \tag{16}$$

where, k is the Epanechnikov kernel with the bandwidth parameter h, δ is the Kronecker delta function, C is the normalization constant, and x_0 are the center coordinate, $b(x_i)$ is the histogram function that assigns color or gradient at the location x_i.

$$\rho[q(x_0), p] = \sum_{n=i}^{N} \sqrt{q(x_0)p(x)} \tag{17}$$

5. Experiment and analysis

We choose two representative videos that possess characteristics like low contrast, intensity inhomogeneity and complex backgrounds. In Video 1, the video has 133 frames. The first 73 frames of the video are in smooth motion, and the abrupt motion starts at frame 74. In Video 2, the video possesses 156 frames, and abrupt motion begins at frame 142. We use three algorithms to track the Ochotona curzoniae in two videos: 1) the particle filter algorithm(PF); 2) the improved motion model of the particle filter algorithm (IM-PF); 3) the proposed method.

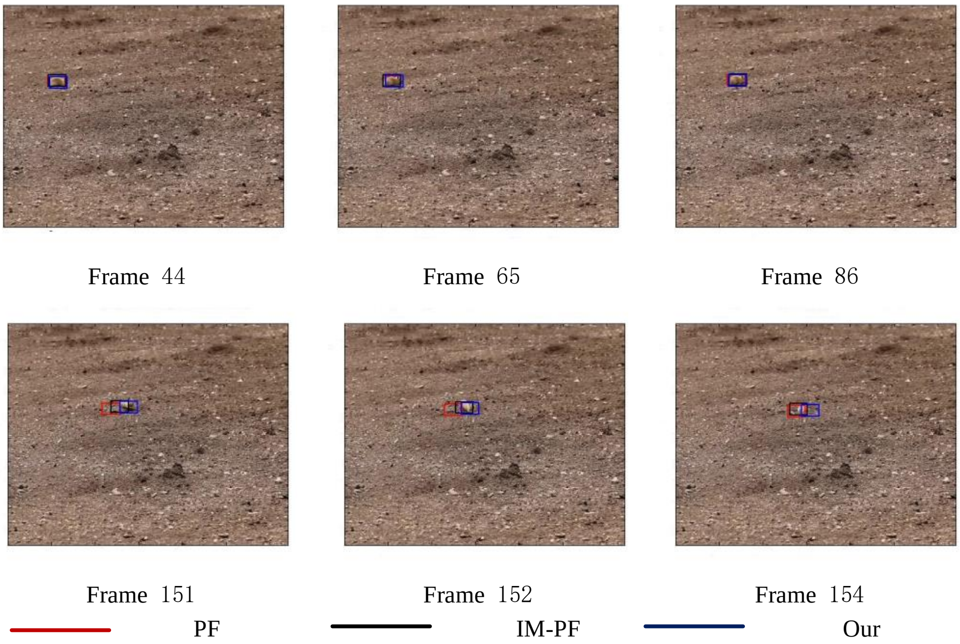

Figure 1. Tracking result of Video 1.

As is shown in Fig. 1, when the object in Video 1 moves fast and changes position suddenly, the PF algorithm is interfered with by the low contrast background. The IM-PF algorithm could improve a lot by improved motion model, but it is not obvious, because the color feature could not handle the low contrast background. The proposed method could solve this problem, and it could locate and track the target successfully. As is shown in Fig. 2, the IM-PF algorithm has a better performance than the PF algorithm, because of the multi-feature fusion observation model, however the proposed method perform better than the other methods.

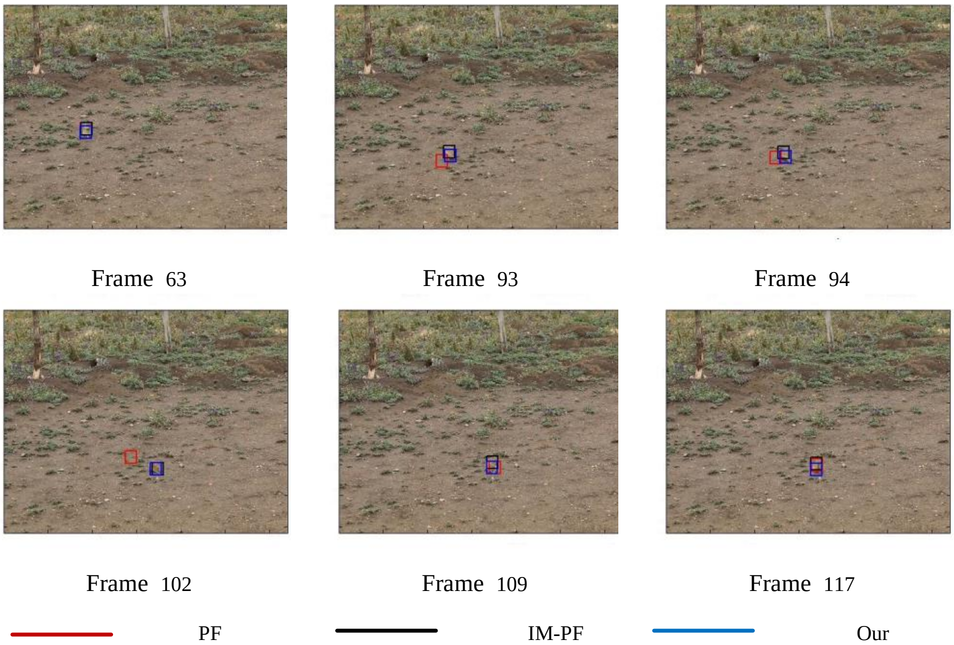

Figure 2. Tracking result of Video 2.

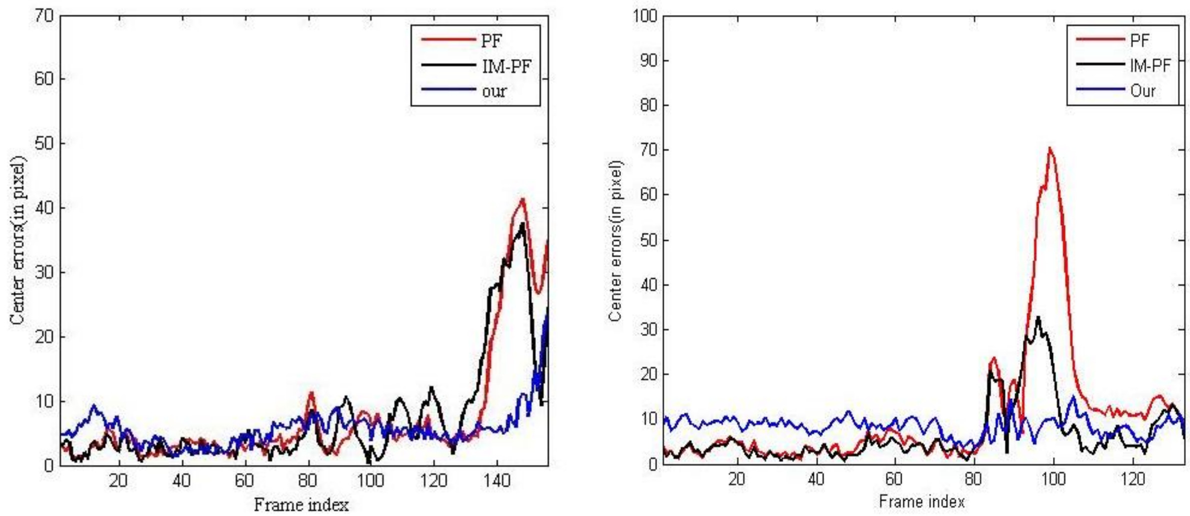

Figure 3. Center errors of Videos

Table 1. RSME of three algorithms.

	PF	IM-PF	Our
Video1	18.0233	9.6233	6.6911
Video2	12.3236	10.3953	6.3782

Table 2. Center errors of the three algorithms.

	PF	IM-PF	Our
Video1	90.29%	93.98%	100%
Video2	89.10%	89.10%	95.51%

In this study, we use RSME, Center errors, and Success rates to quantify the quantitative results. The results are shown in Figs. 3, Tables 1 and 2. As shown in Figs. 1 to 3. The proposed method is robust to the abrupt motion of Ochotona curzoniae, and has better tracking performance when abrupt motions occur. In addition the tracking errors are smaller than the other method, and it has a higher success rate than the other methods.

6. Conclusion

The particle filter algorithm is insufficient for tracking abrupt motion for several reasons: 1) The motion model of particle filter algorithm is a simple motion vector, and it only considers the position information and speed information. To solve this problem, we introduce acceleration information to the motion model; 2) color feature is not suitable for the targets in low contrast backgrounds. We introduce the gradient feature to the color feature as observation model, and the observation model is robust to a low contrast background. The experimental results show that the proposed method has a higher accuracy rate and greater robustness, and we found that the proposed method could track the abrupt motions of Ochotona curzoniae more accurately than the other methods.

Acknowledgments

This research is supported by the National Natural Science Foundation of China(61362034,61841107).

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