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APPLICATION AND EFFECT EVALUATION OF INFORMATION TECHNOLOGY IN PHYSICAL EDUCATION

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Abstract. The Kalman filter and extended Kalman filter algorithm are widely used in physical education video processing, but their performance still needs to be improved for complex backgrounds or high dynamic targets. This paper presents an interactive multi-model algorithm. The displacement detection Kalman filter is used to track moving objects. This method can solve the problem of a single model not being able to match the motion features well. Finally, the simulation experiment of football match video proves that the proposed method can significantly improve the tracking accuracy of moving objects in video.

Key words: Sports video; Interactive multimode algorithm; Debiasing measurement Kalman filter; Moving target tracking

1. Introduction. Physical education programs have more audiences and higher ratings. Many researchers at home and abroad began to conduct in-depth research on moving objects in video to accelerate the acquisition of exciting, dynamic video. Tracking and detecting movement objects in video is an integral part of sports video research, and tracking athletes' movement trajectories can improve the effectiveness and scientific of physical exercise. Structured research on mobile video must be built on tracking and detecting moving objects, so tracking moving objects is an integral part of mobile Video [1]. The core idea is to quickly and accurately capture moving objects utilizing image processing and video analysis. The motion characteristics of the object are also changing dynamically [2], and the existing single modeling method is bound to have a specific deviation from the dynamic model of the real object [3]. This makes the single-mode method based on the Kalman filter easy to appear errors, resulting in following, out-of-step and other problems. This cannot get an accurate tracking effect. The interactive multi-model algorithm is a suboptimal multi-model optimization method developed by Bolm. This method assumes that the migration between modes satisfies the Markov chain with a given migration probability, which can effectively overcome the defects of a single migration mode.

The background of this project is a sports video. Then, the speed and direction of moving objects change rapidly, and the movement path is irregular. Then, a moving target tracking method based on the Kalman filter and an interactive multi-model algorithm is proposed. Firstly, the observation Kalman filter processes the sensor signal [4]. The modeling and weight adjustment of the sensor network are realized using Markov transfer probability. In traditional methods, the interactive multimode method is used to overcome the time delay of parameter identification and variable scale filter [5]. In this way, dynamic tracking of the whole maneuvering target is realized. The traditional Kalman filtering method currently cannot deal with the motion trajectory in the nonlinear case. It has the disadvantages of significant linearization error, low precision and easy divergence. The Kalman filter method of binary debiasing observation can overcome the nonlinear problem of the traditional method well and improve the system's tracking accuracy.

2. Overall structure and workflow of the system. The hardware of the monitoring system includes a PC, serial connector, Infinova integrated fastball and Yunke image acquisition board. The integrated fast ball instrument collects the monitoring image, and the image acquisition board is transmitted to the computer [6]. The computer uses software to parse, process and generate control signals. Then, the command is issued through the serial port to control the speedball to detect and track moving objects. There are three external

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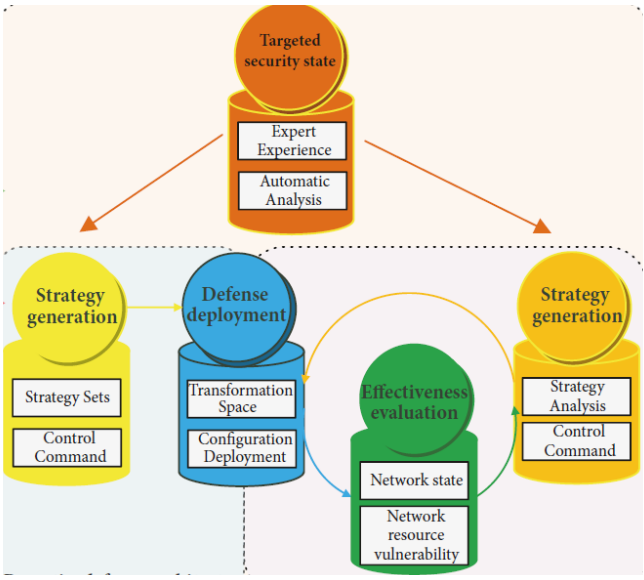

Fig. 2.1: *Hardware structure.*

devices in the design of the hardware platform. One is the input device represented by the CCD camera and the video acquisition card. One is the output device represented by the PTZ control. One is the RS-485 communication device that transmits the obtained images to the computer for detection and tracking [7]. The hardware part of the system mainly includes the image acquisition, control and communication of the PTZ. The hardware architecture is shown in Figure 2.1 (image cited in Moving Target Defense Techniques: A Survey).

The combination of a CCD camera and a cloud-available video acquisition board completes the structure design of the system. By using the C800-4 video capture card from Yunco, non-destructive images can be transferred directly to the graphics card [8]. It can monitor the scene from a distance and rotate, zoom and magnify the camera. The system has two display modes: PAL and NTSC. The picture resolution reaches 720×576 pixels, with 24-bit color. Picture speed up to 25 f/s. The camera uses the Infinovav1700A series fastball. Its optical focal length is 23x, and a corresponding 12x digital zoom can be selected. One hundred twenty-eight preset bits and four pattern scanning modes can be set to facilitate the monitoring of specific locations. The user can control any speed of the ball in the 0.5 to 240 degrees/second range. It can be adjusted according to Pelco-P/D protocol. The control and communication part of the head uses the RS485 serial interface to connect the computer with the integrated fastball and send corresponding commands to it. Using Pelco-D communication mode, high-speed movement in 9600 units. The system is developed in VC++ [9].

The DM642 initialization module is used to initialize the memory interface of the DM642 chip, peripheral device selection module, interrupt module, etc. After the completion of the initialization of the system, it does not need DM642CPU interference, but the DM642CPU is the core of the cycle work, including moving object detection and moving object tracking in two parts.

The theory and technology system of moving object tracking is established based on the Kalman filter and multimode interactive algorithm. Moving object tracking is realized by combining the Kalman filter and multimode interactive algorithm. Figure 2.3 shows the algorithm flow.

Firstly, the location of the object to be tracked in the moving video is selected, and then the gray vector of the object and background near the tracked object is extracted, and the corresponding feature vector is obtained respectively [10]. The Kalman filter processes the image. The classifier discriminates the object to be tracked in the next dynamic video and its background image, and the corresponding confidence graph is obtained. The algorithm uses the interactive multimode algorithm to locate the object in the frame to obtain the object's position and the corresponding background image. Determines whether the image of the moving

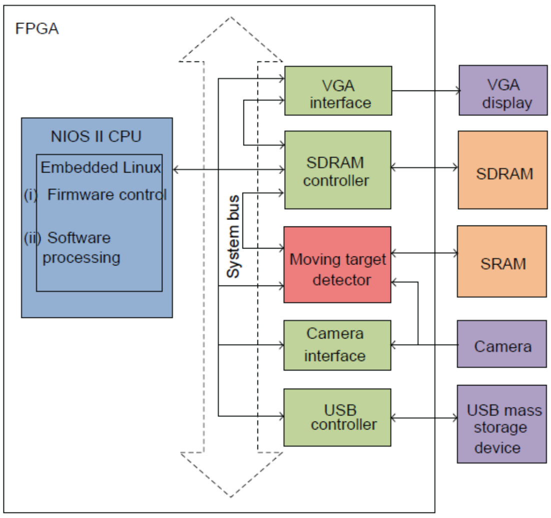

Fig. 2.2: *System program flow.*

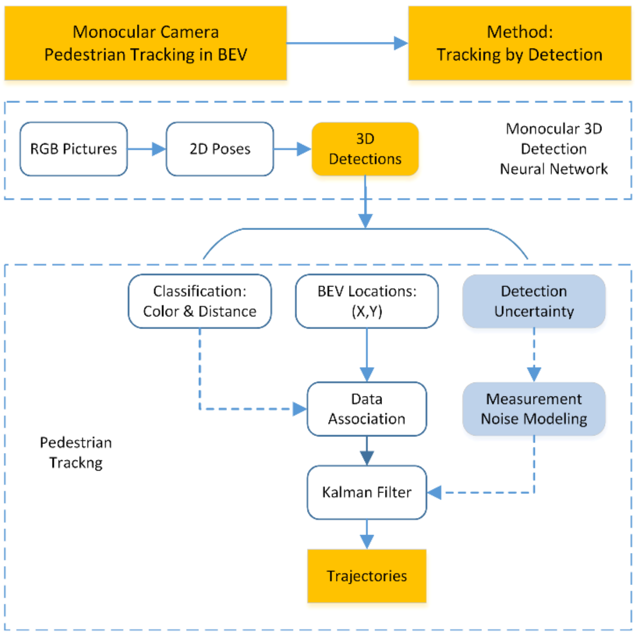

Fig. 2.3: *Video moving object tracking flow based on debias conversion measurement of Kalman filter and interactive multiple models.*

image is tracked in the previous frame [11]. If the previous image is not tracked, the Kalman filter needs to be modified using this moment's object and background pixels. The following image is then tracked until the complete tracking is complete.

3. Debiasing Kalman filter. Israeli scholar Bar-Shalom et al. proposed a depolarization method based on the Kalman filter, which converts the measured data in polar coordinates into orthogonal coordinates [12].

The mean and variance in the cartesian coordinate system were obtained utilizing statistics. Then, it is solved by the Kalman filter under unified cartesian coordinates. This method eliminates the approximation problem, improves the tracking accuracy and ensures the system's stability. The interactive multi-model method has many standard modes: constant speed, acceleration, steering and "current." According to the movement of the object, each model has its representation.

3.1. Target state and observation equation. Firstly, the camera's attitude is taken as the starting point, and the sampling time T is taken as the observation object [13]. The actual distance between the object and the camera is r. The azimuth is θ. The observation is $Z^p = \begin{bmatrix} r_m & \theta_m \end{bmatrix}^T$. The deviation of the measurement at point r_m, θ_m is $\tilde{r}, \tilde{\theta}$. They're all zero averages of Gaussian white noise. Their variance is $\sigma_r^2, \sigma_\theta^2$. The observation formula is as follows

$$Z^p(k) = h(X(k)) + V^p(k)$$

The state variable $h(\cdot)$ is nonlinear.

$$V^p(k) = \begin{bmatrix} \tilde{r}(k) & \tilde{\theta}(k) \end{bmatrix}^T$$

3.2. Average and deviation of observations when converted to rectangular coordinate system. The observed data is transformed into an orthogonal coordinate system represented by

$$x_m = (r + \tilde{r}) \cos(\theta + \tilde{\theta})$$

$$y_m = (r + \tilde{r}) \sin(\theta + \tilde{\theta})$$

position coordinate of the object in the rectangular coordinate system is (x, y). $(\tilde{x}, \tilde{y})$ represents the observed error. Find the observed deviation in the rectangular coordinate system

$$\tilde{x} = x_m - x = r \cos\theta(\cos\tilde{\theta} - 1)$$
$$\tilde{y} = y_m - y = r \sin\theta(\cos\tilde{\theta} - 1)$$

Since all $\tilde{r}, \tilde{\theta}$ are zero-average Gaussian white noise. The observed deviation is removed to obtain the inverse deviation observation at the k time point in the cartesian coordinate system

$$Z(k) = \begin{bmatrix} Z_x(k) \\ Z_y(k) \end{bmatrix} = \begin{bmatrix} r_m(k) \cos\theta_m(k) \\ r_m(k) \sin\theta_m(k) \end{bmatrix} - \mu(k)$$

The average error of the target position observed in the rectangular coordinate system is

$$\mu = \begin{bmatrix} E[\tilde{x} \mid r_m, \theta_m] \\ E[\tilde{y} \mid r_m, \theta_m] \end{bmatrix} = \begin{bmatrix} r_m \cos\theta_m \left(e^{-\frac{\sigma_\theta^2}{2}} - e^{-\sigma_\theta^2} \right) \\ r_m \sin\theta_m \left(e^{-\frac{\sigma_\theta^2}{2}} - e^{-\sigma_\theta^2} \right) \end{bmatrix}$$

By unifying the observation formula with the equation of state, a new observation formula is obtained:

$$Z(k) = HX(k) + v(k)$$

The linear observation matrix is as follows

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

$v(k) = \begin{bmatrix} v_x(k) \\ v_y(k) \end{bmatrix}$ is zero mean noise after removal. The variance is $R(k)$.

Fig. 5.1: *Tracking results of moving objects in the proposed method.*

4. Interactive multi-model algorithm. Take $\hat{X}_{j0}(k/k), P_{j0}(k/k)$ and observed $Z(k)$ as inputs [14]. The interactive multimode algorithm obtains the filtering value at k time. The recursive cycle of the interactive multimodal filtering algorithm consists of the following three steps:

4.1. Mixing.

$$\forall i, j \in M_f$$
$$\mu_{ij}(k-1/k) = \frac{1}{\bar{c}_j} p_{ij}\mu_i\left(\frac{k-1}{k}\right)$$

$\bar{c}_j = \sum_i p_{ij}\mu_i(k-1)$ is the standardized coefficient. $\mu_{ij}(k-1/k-1)$ is a confounding possibility.

4.2. Filtering.

$$X_j(k/k-1) = \frac{(k-1)\cdot X_{j0}(k-1/k)}{\Gamma_j(k-1)\cdot \bar{V}_j(k-1)}$$

$r_j(k)$ is the residual. Where $N(\bullet,\bullet,\bullet)$ is Gaussian dense. $S_j(k)$ represents the variance of the residual. Where $\Lambda_j(k)$ is an expression for probability. T is the time of a cycle. The output of the entire filter is the weighted average of the estimates of multiple filters. Weighting refers to the probability of accurately characterizing the target at a particular time [15]. When the pattern is dominant, the probability is higher than 0.9 and tends to 1 , while when it is dominant, the probability is minimal.

5. Experimental results and analysis. With the video of Guangzhou R&F and Dalian Yifang as the research sample, the Kalman filter and multimode interactive tracking technology were used to track 77 players, and the algorithm's feasibility was discussed. Figure 5.1 shows the tracking results of this algorithm on a series of subject images, while Figure 5.2 shows the effect of tracking a series of subject images with the Kalman filter [16]. The algorithm in this paper can accurately track moving objects in 16, 29, 36, 49 and 81 frames. Experimental results show that the algorithm effectively tracks moving objects in sports videos.

The number and time of iterations tracked using both methods were monitored [17]. The results are shown in Table 5.1. Compared with the traditional Kalman filter algorithm, the proposed algorithm can track the dynamic target in the actual scene, reduce the number of iterations, shorten the tracking time, and improve the system's tracking accuracy.

6. Conclusion. A method of tracking motion trajectory based on interactive multimode and Kalman filter is proposed to realize automatic tracking of motion video objects aiming at ball motion objects in motion

Fig. 5.2: *Kalman filter method moving target tracking results.*

Table 5.1: *Tracking Performance Comparison.*

Evaluation index	Textual method	Kalman filter method
Number of frames per frame	125	125
Number of iterations/times	99	292
Number of iterations per frame	0.82	2.43
Tracking time /s	12.58	27.48
Single frame time /s	0.10	0.23

video recording. Adjusting the camera can ensure that the object is always in the field of view so that the individual object can be automatically detected and tracked adaptively. On the premise of ensuring the overall performance, the problems of illumination and noise are effectively solved, and the system's overall performance is improved. The method proposed in this paper applies to various types of ball images and multiple moving objects in complex scenes. The experimental results show that this method has a high detection rate and fewer false alarms.

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