Kalman Filter-based Signal Processing for Robot Target Tracking

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***Abstract*—In the field of computer vision, the signal tracking of moving objects is a highly representative problem. Therefore, how to accurately and quickly track the target unit has become the focus of the research. Based on this, a Cam Shift algorithm improved by Kalman filtering algorithm is introduced to realize fast tracking of moving targets. This method uses the prediction function of the Kalman filter to predict the moving target of the next frame, transforms the global search problem into a local search problem, and improves the real-time performance. The experimental results show that, in the case of complete occlusion, the trajectory of the unimproved algorithm will deviate compared with the actual trajectory of the improved trajectory tracking curve, but the improved algorithm has no trajectory deviation. The error of the improved algorithm is about 4%, while the maximum error of the unimproved algorithm is about 90%. The improved algorithm reached the expected target accuracy after 110 and 78 trainings in X and Y coordinates, respectively, while the CamShift algorithm without Kalman filtering still failed to reach the expected error after 200 trainings in X and Y coordinates. This indicates that the performance of the improved CamShift algorithm based on Kalman filter has been greatly improved. In conclusion, the improved algorithm proposed in this study is highly practical.**

Keywords—Motion target tracking; Kalman filter; CamShift algorithm; occlusion processing

I. Introduction

The research object of moving target tracking is video sequence, or image sequence, which refers to the spatial-temporal changes of the moving target in the whole sled [1], such as the appearance and disappearance of the target, the position, size and shape of the target, etc. [2]. It is caused by the presence of illumination changes, background interference, shadows, camera jitter, and occlusion between moving signals. Therefore, it is necessary to process the video image sequence [3]. The research on tracking technology of moving targets in the sequence image is to organically combine image processing, automatic control, information science and other technologies to form a fast detection of moving targets from the image information, and to extract the location information of the target for real to ground tracking [4]. Vision is the most important organ of human perception, and it is the main way for humans to obtain external information. With the rapid development of information technology in the 21st century [5], the demand for multimedia information is increasing, and computer vision technology is gradually becoming a hot spot in today's computer research [6]. Computer vision is a comprehensive and interdisciplinary discipline involving numerous aspects such as image processing, intelligent pattern recognition, artificial intelligence, automatic control, and neural networks [7]. Research in computer vision aims to enable computers to sense and understand the external environment, so that they can simulate human vision [8]. Motion target tracking is an important topic in the field of computer vision [9], which focuses on detecting, locating and tracking targets in video frames, obtaining the motion characteristics of the targets, and further processing and analyzing them to achieve higher-level tasks [10]. Based on this, the research aims to propose a Kalman filter-based signal processing algorithm for robot target tracking. The second part is a review of the current status of domestic and international research on Kalman filter-based robot target tracking signal processing algorithms. The third part is the pre-processing of sound signals and the construction of a model for a neural network-based smart home interactive speech fuzzy enhancement algorithm, and the fourth part is the performance analysis of Kalman filter-based robot target tracking signal processing applications.

In this study, Kalman filter algorithm is used to improve CamShift algorithm, and a robot model based on wheel incomplete constraint is proposed, which is taken as a marker column. In the real robot test, the object motion model based on the velocity model is established based on the odometer motion model and the linear characteristics as the background. Finally, the experimental results are analyzed to verify the accuracy of the model tracking ping pong ball. This study chose this algorithm because in the field of computer vision, signal tracking of moving objects is a representative problem, and how to accurately and quickly track target units has become a focus of research. Compared to other algorithms, this algorithm is improved by the Kalman filter, which can use the prediction function to predict the moving target of the next frame, transforming the global search problem into a local search problem, and improving real-time performance. The experimental results show that compared to the unimproved algorithm, the improved algorithm has higher accuracy, smaller error, and no problem of trajectory deviation. Therefore, this algorithm exhibits superiority in moving object tracking. The main contribution of this study is to propose a robot target tracking signal processing algorithm based on a Kalman filter, which can effectively avoid the impact of factors such as lighting changes, background interference, shadows, camera shake, and motion signals on moving target tracking. Compared with other methods, the algorithm in this study has higher real-time performance and accuracy, and can better adapt to different environments and scenarios. In addition, this study also proposed a robot model marked by incomplete wheel constraints, and established an object motion model based on velocity model, providing a more complete and accurate description for robot target tracking. In the experiment, this study also conducted tests on table tennis movement, and verified the accuracy and practicality of the model tracking table tennis through the analysis of the experimental results. In summary, the innovation and practicality of this study can provide new ideas and methods for the research and application of robot target tracking.

II. Related Work

The reason why motion target tracking techniques have evolved and developed so well is by no means a one-off and has been explored in depth in recent years to advance the field. By integrating the extended Kalman filter (EKF) and direction-of-arrival (DOA) based geolocation into a factor graph (FG) framework, Cheng et al. [11] proposed a new location tracking algorithm. The study also proposed the use of a predicted Cramer-Rao lower bound (P-CRLB) to dynamically estimate the observation error variance, exhibiting more robust tracking performance than methods using only a fixed mean variance approximation. By considering the uncertainty of the network and the target A reliable sensor selection method with, Anvaripour et al. [12] proposed an updated traceless Kalman filter (U2KF) to achieve effective tracking of the target through sensor selection, and the results of the study verified the effectiveness and practicality of the proposed scheme. Wang et al. [13] proposed how to unify the coordinate system and data when using multiple sensors for tracking case and data pre-processing. Then, the method of combining fuzzy sets with a novel trajectory optimization method based on the extended Kalman filter (EKF) and nested probabilistic numerical linguistic information (NPN-EKFTO) is investigated and the feasibility of their method is verified with a study case of unknown maneuvering target trajectory optimization in Sichuan Province. Zhou et al. [14] proposed to study the target and pursuit satellite approach operation between the target and the pursuing satellite for the positional tracking control problem, and proposed an updated controller which has better adaptive capability for the initial estimation of inertial parameters as this updated controller estimates the pursuer's inertial parameters through UKF, and finally numerical simulations are given to prove the effectiveness of the proposed controller. Zhao et al. [15] proposed a new adaptive square root volumetric joint probabilistic data association (ASRCJPDA) and constructed a virtual vehicle target tracking scenario in PreScan software to better simulate real traffic conditions. The simulation of the target tracking example showed the effectiveness and superiority of the method.

Shmaliy et al. [16] modified the KF and unbiased finite impulse response (UFIR) filters using a backward Eulerian (BE) method for models with colored measurement noise (CMN). This method is more suitable for systems without feedback. The study showed that the equivalence of the KF algorithm was demonstrated analytically and confirmed by simulations, giving numerical examples of target tracking and providing visual object tracking for experimental validation, demonstrating the high efficiency of the designed algorithm in CMN removal. Yang et al. [17] proposed a novel and effective method to investigate further applications of algebraic filtering processing, including Gaussian filtering for background removal and extended Kalman filtering for target prediction, to maintain the advantage of real-time tracking. Blair [18] found that when tracking maneuvering targets using a near-isovelocity (NCV) Kalman filter with discrete white noise acceleration, the choice of process noise variance is complicated by the fact that process noise errors are modeled as white Gaussian and target maneuvers are deterministic or highly deterministic. The study provided information on the use of the NCV Kalman filter for the NCV. Bhat et al. [19] proposed a particle filter-based tracking algorithm to track targets in vivid and complex environments in video, based on the similarity between features extracted from the target and possible candidate features in consecutive frames, using a particle filter algorithm to build the target's trajectory. For the color distribution model, Bhattacharya coefficient is used as a similarity metric, and the nearest neighbor distance ratio is used for matching the corresponding feature points in the KAZE algorithm. The study shows that the performance of the proposed tracking scheme is significantly better than contemporary feature-based iterative target tracking methods. Fraser and Ulrich [20] solved the NEO spacecraft formation mission by designing two unique adaptive extended Kalman filter algorithms for relative navigation problem. The proposed adaptive Kalman filter approach uses maximum likelihood estimation techniques to derive analytical adaptation laws. The study shows that the proposed adaptive navigation algorithm is significantly more robust in filtering initialisation errors, dynamics modeling defects and measurement noise.

The research on robot target tracking signal processing based on Kalman filtering by domestic and foreign scholars shows that there are more studies on Kalman filtering tracking, but there are relatively few studies on the fusion and optimisation of Kalman filtering and CamShift algorithms to achieve signal processing for robot target tracking and signal recognition of obscured targets. Thus, this study focuses on the fusion of Kalman filtering and CamShift algorithms for robotic target tracking signal processing, which improves the recognition rate compared to a single algorithm and also significantly enhances the recognition of occluded targets during motion.

III. Development of a Kalman Filter-based Approach to Robot Target Tracking Signal Processing

A. *Development of a Mathematical Model for Robot Target Tracking Signal Processing based on Kalman Filtering*

In order to accurately determine the specific position of a moving object at each time to achieve the purpose of tracking, the object being tracked can be extracted from the feature points, which can be a simple geometric figure, a three-dimensional point, or the centre of a solid, so that the analysis of a target is transformed into the analysis of data from certain specific points. Since the study takes the observation information acquired by the camera about a moving object as angular information, the equation for the observation of a moving object is shown by Equation (1).

$$\beta = \arctan(\frac{x}{y}) + \omega = h(x, y) + \omega \tag{1}$$

In Equation (1), x and y are the positions of the target points in the x and y directions of the coordinate axes, and ω is the observed noise with a mean value of 0 and a mean variance of σ_{β}^{2}. In order to determine the information about the direction of movement, i.e. the position and velocity of the object, to make the state vector $s(t)$, the state at the moment of t is shown in Equation (2), and the noise effect is shown in Equation (3).

$$s(t) = \begin{pmatrix} x \\ y \\ v_x \\ v_y \end{pmatrix} \tag{2}$$

$$\dot{s}(t) = Fs(t) + W \tag{3}$$

In Equation (3), $F = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$ is its constant coefficient matrix and W is its dynamic noise. Since the observations of camera observation are obtained from each frame, Equation (3) is discretized as shown in Equations (4) and (5).

$$s_k = F_T s_{K-1} + W_{K-1} \tag{4}$$

$$F_T = e^{FT} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

In Equations (4) and (5), T is the sampling period, and W is the noise at the K sampling. After linear discretization, the observed equation of state is shown in Equations (6) and (7).

$$Z_K = H_K s_K + V_K \tag{6}$$

$$H_K = \left[\frac{y}{x^2+y^2}, \frac{-x}{x^2+y^2}, 0, 0 \right] \| S_{K/K-1} \tag{7}$$

In Equations (6) and (7), V_K is the noise of the system at the time of K sampling and H_K is its coefficient matrix.

X_W Theand Y_W axes in an arbitrarily set world coordinate system are parallel to the image coordinate system x and y axes respectively, so that the X_W and Y_W axes are parallel to the pixel coordinate system u and v axes respectively. At this point the robot is moving horizontally, so the coordinates of the Z_W axis do not change and therefore the coordinates of the Z_W axis can be ignored for the purposes of the study. In addition, the camera model on the robot is a pinhole model, which is made according to the principle of transmission projection, in a plane parallel to the $X_W O Y_W$ plane, by which the angle can be observed. This angle signal is then transmitted to the Kalman filter module to estimate the position of the tracking target.

B. Establishment of A Kalman Filter-based Signal Processing Method for Robot Target Tracking

Image signal pre-processing work is crucial in the robot target tracking process, based on this, the image pre-processing, can effectively remove noise, reduce the effect on the subsequent processing, improve the accuracy of the detection algorithm, image pre-processing techniques include color image filtering, color image grayscale and binarization, image post-processing is mainly to eliminate interference to the image, thus obtaining a satisfactory image. The post-processing of the image is the elimination of interference to obtain a satisfactory image. Post-processing of video images is the study of mathematical morphological operations and histogram conversion of images. The acquisition, input and processing of images generate noise at every step of the process. Noise can lead to degradation and blurring of the image quality and seriously affect the important characteristics of the image, which causes increased difficulty in the analysis and understanding of the image, especially in the image acquisition and input process. Therefore, the role of noise suppression is particularly prominent [21]. The specific steps are shown in Fig. 1.

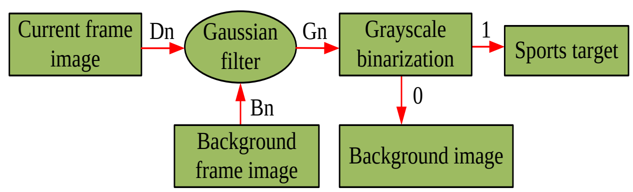


Fig. 1. Image preprocessing steps diagram.

Gaussian filtering is a smooth linear filter and the weight of the template is taken into account when selecting the Gaussian function. The algorithm can effectively filter Gaussian noise, and it is particularly effective in normal conditions. The two-dimensional Gaussian function is shown in Equation (8).

$$h(x.y) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{x^2+y^2}{2\sigma^2}} \tag{8}$$

In Equation (8), the amplitude of the Gaussian filter is determined by the parameter σ. Rotational symmetry is an important property in a two-dimensional Gaussian function that ensures that the filter is equally smooth in all directions. In addition, an important property of the Gaussian function is that the Gaussian function is a single function and the Gaussian filter is essentially a weighted average filter, which can be expressed as shown in Equation (9).

$$g(x,y) = \sum_{m=-K}^{K} \sum_{n=-L}^{L} W(m,n) f(x+m, y+n) \tag{9}$$

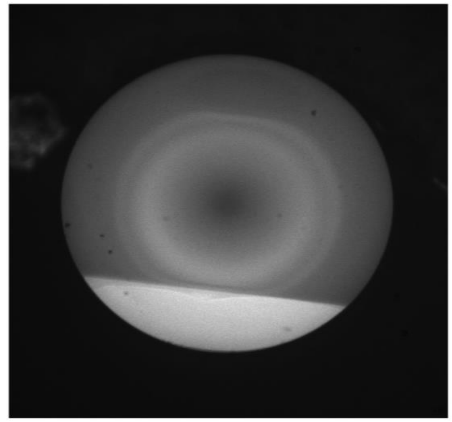
In Equation (9), $W(m,n)$ is its weighting factor and the viewport of the Gaussian filter is $(2K+1)\times(2L+1)$. Mean filtering is essentially a process where the target pixels are first set as a template (the template is the removal of the target pixels and consists of 8 pixels) and the mean of the pixels in the template is replaced with the target pixels again, as shown in Equation (10).

$$g(x,y)=\frac{1}{(2K+1)(2L+1)}\sum_{m=x-K}^{x+K}\sum_{n=y-L}^{y+L}f(x,y) \tag{10}$$

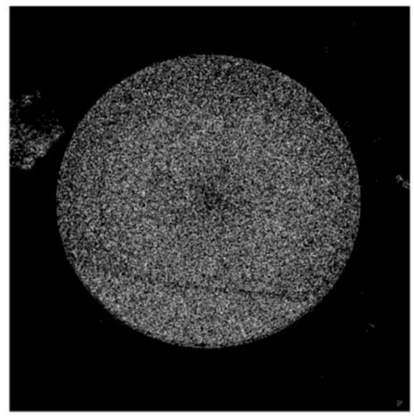
Grayscale binarization refers to setting the grayscale value of the pixels of the original grayscale image to 0 or 255, and converting the grayscale image into a black and white image with only all white. Choosing a suitable threshold that can convert 256 different grayscale images into a binary image, the obtained binarized image still has good local features and overall features. The pixels in the grayscale image are divided into all black or all white according to the set threshold The selection of a suitable threshold is an important step in this process. The set threshold can be used to segment the target from the background when detecting moving objects, and the processing of the grey-scale image binarisation is shown in Equation (11).

$$g(x,y)=\begin{cases}1, f(x,y)\geq \tau \\ 0, f(x,y)\leq \tau\end{cases} \tag{11}$$

In Equation (11), $f(x,y)$ represents the greyscale value of (x,y) in the initial greyscale image and $g(x,y)$ represents the greyscale value of the pixel (x,y) after conversion to a binary image. First, a suitable threshold τ is set, which is compared to τ . The pixel is white if its grey value is greater than the threshold τ and black if it is below the threshold τ . Fig. 2 shows the difference between the original table tennis image before and after the grey-scale binarisation pre-processing.



(a) The original image.



(b) Image after grayscale binarization.

Fig. 2. Comparison of table tennis before and after greyscale binarization.

Fig. 2(a) shows the original image of table tennis, and Fig. 2(b) is the image obtained after gray binarization. Image gray binarization means that the gray value of each pixel in the pixel matrix of the image is 0 (black) or 255 (white), that is, the effect of the entire image is only black and white, and the gray value range of the image after binarization is 0 or 255.

Kalman filtering (Kalman) it is an algorithm for minimum variance estimation of a dynamic system state sequence based on an a priori model describing the random variables in the dynamic system, and then a system of KF equations to obtain a best estimate of the target state based on global information in real time. Kalman filtering algorithm includes both state model and observation model [22], as shown in Equations (12) and (13).

$$X_k=A_kX_{k-1}+B_kW_k \tag{12}$$

$$Z_k=H_kX_k+V_k \tag{13}$$

In Equations (12) and (13), X_k is the $n\times1$ dimensional state vector matrix; A_k is the $n\times n$ dimensional state transfer matrix; B_k is its input matrix; W_k is a random vector of dynamic disturbances (white noise); Q is the covariance; Z_k is the $m\times1$ dimensional observation vector set; H_k is the $m\times n$ dimensional observation coefficient matrix, and V_k is the observation noise vector in the covariance dimension R . Based on the above model, the Kalman filter can be divided into two categories, one for algorithmic forecasting and the other for correction of subsequent observations. The detailed process of the algorithm is as follows [23]. Firstly, the state prediction equation of the algorithm is shown in Equation (14).

$$X_k=A_kX_{k-1}+B_kU_k \tag{14}$$

The error covariance forecast equation and the updated Kalman gain factors are shown in Equations (15) and (16).

$$P_k=AP_{k-1}A^T+Q \tag{15}$$

$$K_k=P_kH^T(HP_kH^T+R)^{-1} \tag{16}$$

The covariance correction equation for its state correction and error is shown in Equations (17) and (18).

$$X_k = X_k + X_k(Z_k - HX_k) \tag{17}$$

$$P_k = (I - K_k H)P_k \tag{18}$$

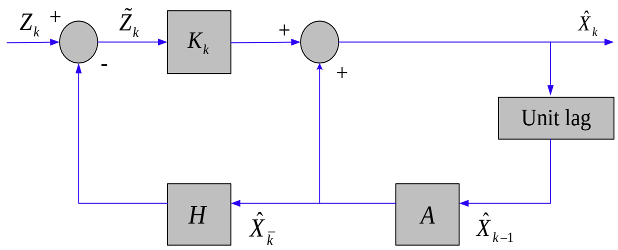


Fig. 3. Block diagram of Kalman filter for stochastic linear discrete system.

Fig. 3 is a block diagram of the Kalman filter for the stochastic linear discrete system (Kalman) obtained from Equations (14) and (17), with the observed variable as the input signal and the resulting optimal estimate as its output signal. Tracking process using Kalman filter: Kalman filter uses the observed value to estimate the motion state. The process is divided into two steps: prediction and update. The prediction part is responsible for estimating the state of the next moment by using the current state and error covariance, and obtaining a prior estimate; the update section is responsible for feedback, taking the new actual observations into account with the prior estimates to obtain a posteriori estimate. After each completion of prediction and update, the priori estimate of the next moment is predicted by the posterior estimate, and the above steps are repeated. The Kalman filter Recursion is the principle. It directly acts on all previous data to estimate the current state value. Thus, Kalman filter is very easy to implement, which is also one of the significant advantages of Kalman filter.

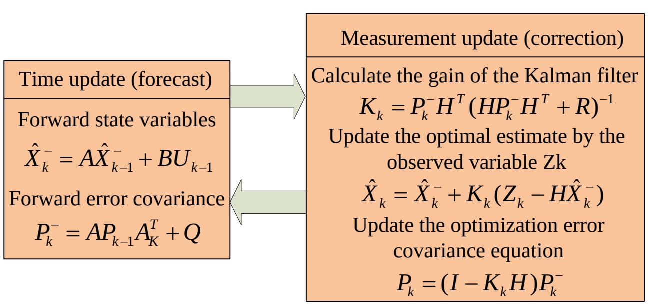


Fig. 4. Kalman filter algorithm flow chart.

On this basis, the posterior estimate derived from the system observation equation and the time update equation is used as the next a priori estimate, which is iterated. The Kalman filter has a recursive repetitive feature that makes it highly time-sensitive, and on this basis, the current state can be recursively estimated from the observed variables and the posterior estimate of the previous point only [24]. The Kalman filter approach can be illustrated in Fig. 4, which divides the Kalman filter into two parts, the measurement update and the time update. In this case, the covariance of the errors can be calculated separately, with $\hat{X}_{k-1}$ and P_{k-1} as their initial estimates. From the theory of Kalman filtering, it was found that when tracking a moving object, the position of the moving object in the next frame can be accurately predicted to reduce the search distance. In the case of partial occlusion, the object can be tracked quickly and accurately, and the algorithm is simple and convenient to enable real-time tracking of the target. The traditional Camshift algorithm is an expansion of the Meanshift algorithm and is currently the most widely used tracking method. This method uses a colour histogram to obtain a color probability distribution which changes as the object moves, allowing the object to be tracked using the change in color probability distribution. The method mainly consists of transforming the sequence image in RGB color space into HSV space and using the H component as the color histogram, so that the size of the random distribution can be visualised. In addition, the inverse projection method is used to obtain the color probability distribution map. In fact the color probability distribution map is a grey scale image. By finding the zero order distance and first order spacing, the distance between the centre of the viewport and the shape centre can be found, so that the essence of the Camshift algorithm is to perform Meanshift operations on each frame to track the target object by repeated iterations [25]. The probability curve of the CamShift algorithm is obtained through an inverted histogram. For the convenience of the study, a normalisation method is prescribed for the histogram, as shown in Equation (19).

$$q = \{q(u)\}_{u=1,2,\cdots,m} \tag{19}$$

In Equation (19), the eigenvalues of $\sum_{u=1}^{m} q(u) = 1$; u refers to indicators of a rectangle in the histogram; m is the number of its rectangles, and the probability value of its u -th square is shown in Equation (20).

$$q(u) = \frac{1}{n} \sum_{(x,y)\in R_m} \delta\left[c(R(x,y)) - u\right] \tag{20}$$

In Equation (20), $R(x,y)$ is the image function of the image block R_m; n is the number of its pixels; (x,y) is the value of the pixels, expressed in coordinates, and $\delta(\square)$ is the Kronecker function; R has the following relationship with the corresponding pixels of its image block I of the same size, as shown in Equation (21).

$$I(x,y) = \sum_{u=1}^{m} q(u)\delta\left[c(R(x,y)) - u\right] \tag{21}$$

In Equation (21), $R(x,y)$ is the image function of the image block R and the image block I. It is a mono which has a glow between [0,1] and must be linear in the range [0,226] in order to meet the display requirements. Both the MeanShift and CamShift algorithms use iterative operations on the weight map in the tracking frame to achieve tracking of objects, but their methods are. MeanShift assigns a weight to each pixel $\sqrt{q_u / p_u}$. q_u and p_u are the current pixel values in the target model and the corresponding probabilities in the candidate patterns, while CamShift assigns a weighting factor to each pixel q_u. Based on the calculation of the target size and colour probability distribution, the centre of mass and size of the moving object in the current frame is found and a circular frame is used to target the moving object. Fig. 5 shows the flow chart of the CamShift tracking algorithm.

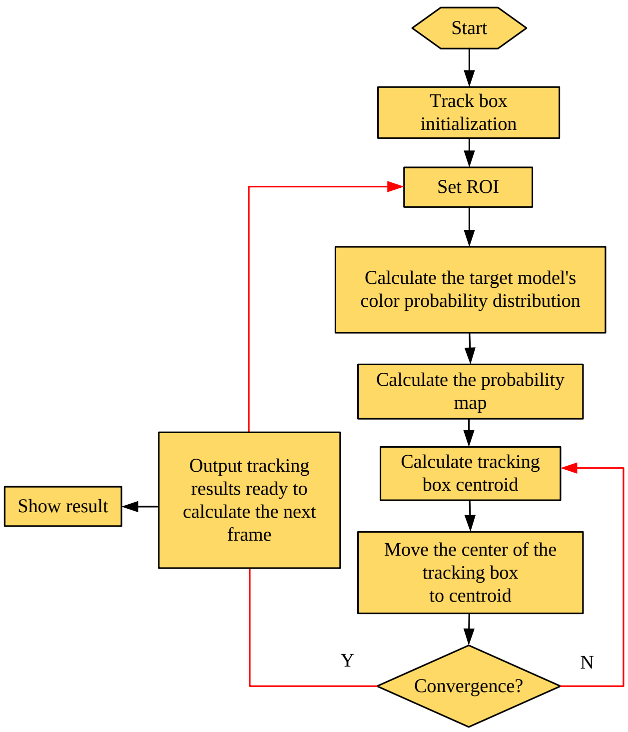
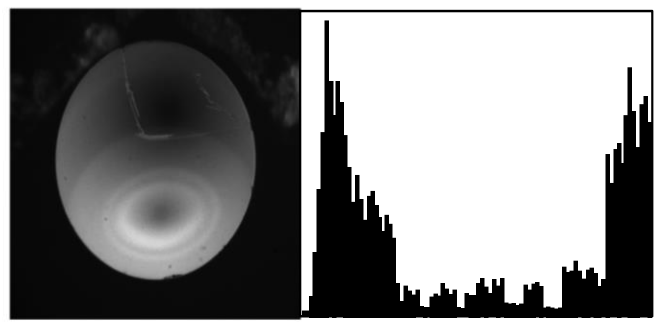


Fig. 5. CamShift tracking algorithm flowchart.

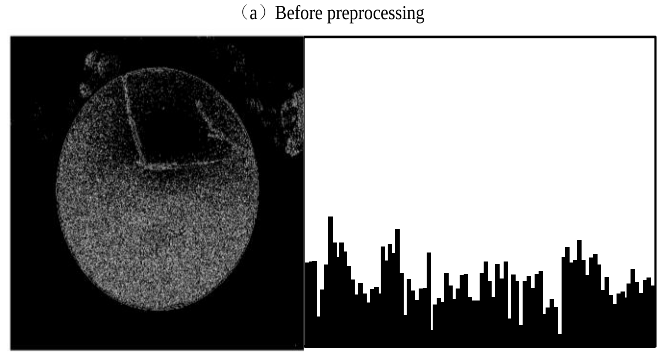
CamShift algorithm can achieve fast tracking of the object and meet the real-time demand. Its specific steps are as follows, the first step is to initialize the size and position of the search window, and the algorithm can be done automatically based on the object detection. The second step is to obtain the probability distribution of the color in the search box. The third step is to set the region of interest (ROI), based on the current object position, size and the maximum of a single frame motion distance. The fourth step is to solve for the centre of mass of the search square using the MeanShift algorithm. The fifth step is to cross out the position of the object if the distance between the centre point and the centre of mass is below a certain threshold. Otherwise, return to the fourth step. The sixth step is to perform adaptive calculations for the orientation and size of the tracked object. As the CamShift motion target tracking algorithm lacks a motion prediction module, the combination of Camshift and Kalman filtering allows the position of the moving object to be effectively estimated using the Kalman filter when the target is partially occluded, the targets are interfering with each other, the target is moving too fast and the tracking fails due to background interference in the approach. The Z_k obtained from the iterations of the algorithm has a great influence in the Kalman filter, thus affecting the prediction of the Kalman filter.

IV. Performance Analysis of Kalman Filtering Based Robot Target Tracking Signal Processing Applications

The experiment adopted 28 frames per second, 360*240 resolution of rolling ping-pong image video. The processor is Intel(R) Core(TM) i5-8250 CPU@1.60GHz, and the memory is 8GB. The OpenCV library is used to detect and track the extracted objects. In order to test the performance of the research algorithm, the study designed a robot to track the motion of table tennis. Based on this, a wheel-based non-complete constraint robot model was proposed and used as a marker column. In the physical robot experiments, based on the odometer motion model and taking the linear characteristics as the background, the object motion model based on the velocity model was established. First, the robot starts with the pre-processing of the captured table tennis images. By pre-processing the images, the method effectively removes noise from the images and reduces the impact on subsequent processing, as shown in Fig. 6.



（a）Before preprocessing



（b）After preprocessing

Fig. 6. Comparison of the effect before and after preprocessing the collected table tennis image signal.

As can be seen in Fig. 6, the histogram of the table tennis image signal captured by the robot changes significantly after pre-processing, which makes the grey intervals of the image larger and more uniform. This increases the contrast and makes the details in the image clearer, eliminating individual noise points to achieve the enhancement effect. Some images have the disadvantage of higher contrast due to factors such as lighting, blurring the details, and comparative suppression of irrelevant grey areas to bring out relevant objects or grey areas. The algorithm proposed in the study explores whether the improved CamShift algorithm based on Kalman filtering can effectively solve the problem of robot tracking of target motion trajectories when moving objects are heavily obscured. 28 frames per second video with 360*240 resolution of a rolling table tennis ball image was chosen for this experiment. The actual motion trajectory and robot tracking of the target trajectory are shown in Fig. 7.

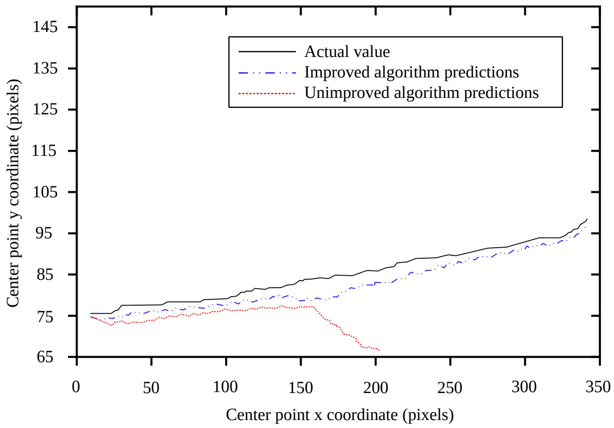


Fig. 7. Comparison of trajectory tracking of occluded table tennis balls before and after the improvement of Kalman filter algorithm.

It is evident from Fig. 7 that the target trajectory signal tracking graphs for the algorithm improved by Kalman filtering and the algorithm not improved by Kalman filtering are compared with the true values of the target. The graph shows that after encountering complete occlusion, the ping pong ball trajectory deviates from the true trajectory under the unimproved algorithm, while the corrected algorithm shows no track deviation with its improved by Kalman filtering. The bullseye coordinates of the CamShift algorithm for target unit tracking are shown in Table I.

TABLE I. THE COORDINATES OF THE TARGET CENTER POINT BEFORE AND AFTER THE IMPROVEMENT OF THE TRACKING ALGORITHM

Frame number	**Target real coordinates**	**Real coordinates before algorithm improvement**	**The real coordinates after the algorithm is improved**	**Algorithms must be improved error**
Frame 7	(100, 74)	(99, 67)	(99, 72)	3.98
Frame 11	(148, 78)	(148, 69)	(143, 75)	4.56
Frame 15	(189, 89)	(181, 56)	(183, 62)	23.66
Frame 18	(208, 84)	(183, 56)	(208, 79)	34.02
Frame 23	(258, 94)	(183, 54)	(246, 88)	90.95

Table I shows the relative error between the improved central position and the actual position during tracking, namely the relative absolute deviation between the two points. It can be seen that the target signal coordinates of Frames 7, 11, 15, 18 and 23 are selected in the research. When the target is blocked, the tracking accuracy of the improved algorithm based on Kalman filtering is greatly improved. The improved method can ensure its tracking accuracy, and its iteration time comparison is shown in Fig. 8.

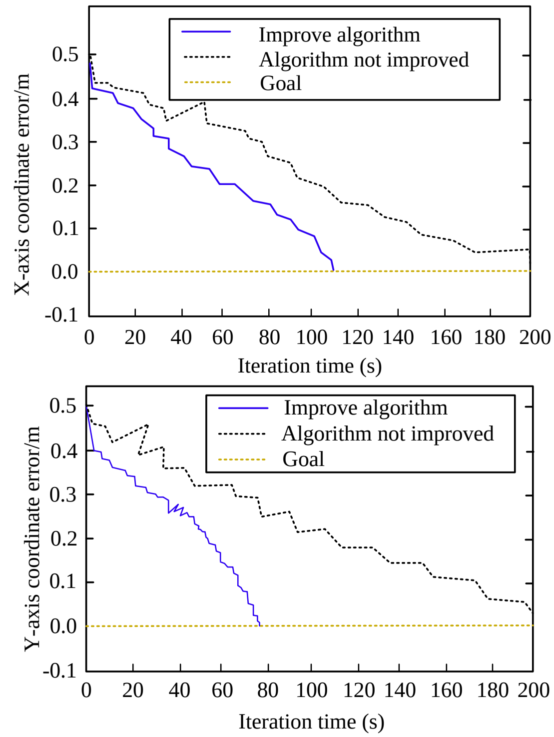


Fig. 8. The variation of the target X, Y coordinate error with time.

Fig. 8 clearly shows that the algorithm improved by Kalman filtering achieves the expected target accuracy after 110 and 78 training cycles for X and Y coordinates respectively, while the CamShift algorithm without Kalman filtering does not reach the expected error after 200 training cycles for both X and Y coordinates, indicating that its training effect is poor. This shows that the CamShift algorithm with Kalman filtering has better performance and can reach the intended training accuracy in a very short period of time.

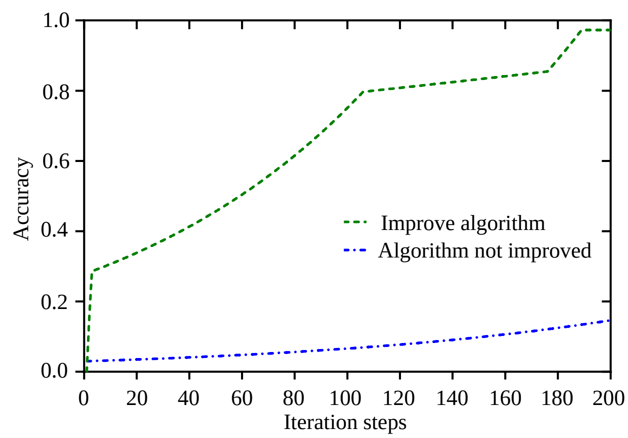


Fig. 9. Comparison of the accuracy of the algorithm before and after the improvement.

As can be seen from Fig. 9, the initial value of the CamShift algorithm improved by Kalman filtering increases with the number of iterations of the model, and its correctness gradually stabilizes when the number of iterations of the model reaches a certain level. After stabilization, the accuracy of the model constructed by the improved CamShift algorithm based on Kalman filter was 99.69%. After 200 iterations, the improved algorithm showed a qualitative improvement in its performance over the previous algorithm, perhaps due to the combination of CamShift and Kalman filter. As a result, the targets were partially occluded, interfered each other, and moved too fast in approaching background interference caused by tracking failure. The position of the moving object can be effectively estimated using the Kalman filter, which affects the prediction of the Kalman filter. Table tennis tracking images are shown in Fig. 10.

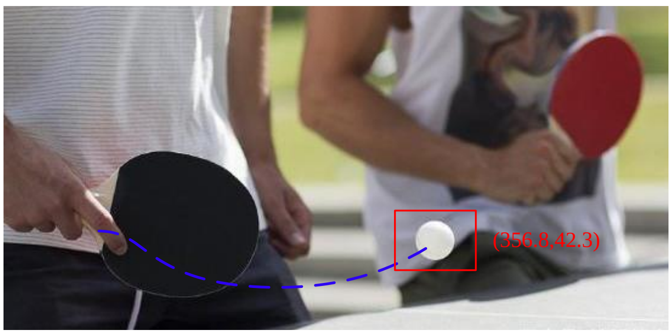


Fig. 10. Table tennis trajectory tracking image.

As can be seen from Fig. 10, the improved Kalman filtering algorithm proposed in this study has an excellent tracking effect on table tennis, with the confidence interval reaching 99%. In the frame 10, the coordinates of table tennis are determined as (356.8, 42.3), and its track tracking effect is excellent, without trajectory deviation and other phenomena. Therefore, the algorithm proposed in this study has excellent practicability.

V. Results and Discussion

The results of this study indicate that the signal processing algorithm for robot target tracking based on Kalman filter has great application potential in solving the difficult problems in moving target tracking. This algorithm achieves fast tracking of moving targets by tracking and predicting target signals, with higher real-time performance and accuracy. In addition, the adaptive ability and robustness of the algorithm have also been well verified. The experimental results show that the improved Kalman filter algorithm can quickly and accurately capture targets when they are occluded, making the tracking of the target continuous and stable, thereby solving the error when the target is occluded in global search and improving real-time performance. Therefore, this algorithm can be widely applied in fields such as robot target tracking, video surveillance, and intelligent transportation.

In addition, this study also has certain reference value for the establishment of robot models. By establishing a robot model marked by incomplete wheel constraints and establishing an object motion model based on the velocity model, a more complete and accurate description of robot target tracking is provided, and it also provides a certain reference for research in other robot application fields.

It should be pointed out that although this study has achieved good results in experimental results, it still needs to be adjusted and optimized according to specific situations in practical applications. At present, research methods have certain limitations in solving the problem of target occlusion. Although the improved Kalman filtering algorithm can quickly and accurately capture targets, if the target is completely occluded, the algorithm still has errors. In addition, the performance of the algorithm may also be affected by specific environments and scenarios, and needs to be adjusted and improved. Therefore, in future research, it is necessary to further improve the robustness and adaptability of the algorithm to cope with more complex practical situations. At present, research has implemented a robot target tracking signal processing algorithm based on Kalman filter, and has achieved good results in experimental results. This algorithm can quickly and accurately capture moving targets, with higher real-time and accuracy, and solves the error of target occlusion in global search. There are two aspects to the unfinished work: on the one hand, adjustments and improvements are made to different environments and scenarios to improve the robustness and adaptability of the algorithm. On the other hand, it is necessary to further improve the real-time and accuracy of the algorithm to cope with more complex practical situations. Therefore, in future research, it is necessary to further optimize and improve algorithms to meet the needs of different scenarios, and explore new methods to improve the performance and practicality of algorithms.

VI. Conclusion

Moving target tracking is an important research direction in computer vision. This paper introduces the principle of Kalman filter algorithm and CamShift algorithm. Kalman filter technology is used to realize target tracking, which makes up for the loss of Camshift algorithm in target tracking. In the case that the target is seriously blocked, the algorithm can capture the target quickly and accurately, and make the tracking of the target continuous and stable, with good adaptive ability and robustness. The research shows that the contrast of the target signal is improved after the preprocessing. The enhancement effect is achieved, and the single noise point is eliminated. By comparing the tracking curve of the target track signal of the improved Kalman filtering algorithm with the real motion curve of the target, it can be seen that, when the target meets the complete occlusion, the ping pong track under the unimproved algorithm deviates from the real track, while the improved algorithm almost coincides with the target motion track. The algorithm improved by Kalman filtering reached the expected accuracy in X and Y coordinates after 110 and 78 training times respectively, while the algorithm without Kalman filtering still did not reach the expected error in X and Y coordinates after 200 training times. The accuracy of the model based on the improved algorithm of Kalman filter is 99.69%. After 200 iterations, the performance of the improved algorithm is significantly improved compared with the previous algorithm, indicating that the proposed robot target tracking signal processing algorithm based on Kalman filter has strong practical significance. This method realizes the fast tracking of moving target, solves the error when the target is blocked in the global search, transforms the global search problem into the local search problem, and improves the real-time performance.

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

It is declared by the authors that this article is free of conflict of interest.

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