

Retraction

Retracted: Moving Target Localization in Sports Image Sequence Based on Optimized Particle Filter Hybrid Tracking Algorithm

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Guo, "Moving Target Localization in Sports Image Sequence Based on Optimized Particle Filter Hybrid Tracking Algorithm," *Complexity*, vol. 2021, Article ID 2643690, 11 pages, 2021.

Research Article

Moving Target Localization in Sports Image Sequence Based on Optimized Particle Filter Hybrid Tracking Algorithm

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This paper proposes a fusion stadium positioning algorithm, which uses self-optimizing particle filter to integrate the improved athlete dead reckoning and WiFi position fingerprint algorithm for stadium positioning. In order to determine the initial absolute position of the stadium positioning, for athletes entering the stadium from the outside, a seamless switching algorithm outside the stadium is proposed, using the characteristics of high-altitude satellite GPS to find a suitable switching point as the initial absolute position. If in the stadium, WiFi static positioning determines the initial absolute position. Then, aiming at the problem that the poorly diversified particles cannot be better integrated and localized, a self-optimized particle filter algorithm is proposed. After resampling and retaining high-weight particles, the characteristics of low-weight particles are embedded in the copied high-weight particles. This can improve diversity, and we finally carry out fusion positioning. The target tracking algorithm based on Mean Shift has a fixed-scale tracking window, and the tracking effect of variable-size targets is not ideal. In this paper, an affine transformation algorithm is introduced to improve it. First, we iterate the adjacent image frames in reverse Mean Shift to determine the center position of the target and then use the corner matching method to perform template matching on the target to adjust the size of the tracking window. Through simulation verification, it is proved that the optimized particle filter hybrid tracking algorithm can achieve the ideal result when the target size changes. For the image sequence S1, the tracking window of the 20th frame and the 40th frame has a small offset, but the optimal position can be quickly found by Mean Shift iteration. For the image sequence S2, between the 40th frame and the 60th frame, the target occlusion causes the accuracy of the target template to decrease, and the Bhattacharyya coefficient is at a relatively low value. For the image sequence S3, the tracking effect of the optimized particle filter hybrid tracking algorithm meets the requirements.

1. Introduction

Because machine vision technology has the advantages of noncontact and long range of action, in recent years, agricultural personnel, factories, hospitals, military, and scientific research institutions have widely used this technology [1]. In industrial production workshops, automated devices tend to be mass-produced. In order to improve work efficiency, machine vision technology will be used to check the quality of the product and measure the size of the product [2]. Noncontact precision measurement and product surface quality inspection based on image processing technology have the characteristics of high accuracy and strong anti-interference ability. In the military field, robots based on machine vision technology can be used to autonomously

drive drones. Since the robot does not have the ups and downs of the psychological state, it can perform standardized operations according to the identified target, which can not only increase the success rate of the mission, but also reduce the casualties of combat personnel [3]. In the field of aerospace, computer vision technology also plays a vital role, allowing humans to better explore space and the universe. With the help of image processing technology, the pictures returned by the exploration satellites are processed. Through denoising and enhancement techniques, the quality of the returned images can be improved and people can better pay attention to the changes in the interstellar movement [4].

Now more and more people are researching how to obtain image video targets or other signals through computers and process them to achieve the expectations that

people want, and this science is called computer vision [5]. Through continuous research, computer vision is divided into many small subjects, and the research of target tracking is an extremely important part of this field. Generally speaking, the process of processing the specified object (including feature extraction, classifier training, and obtaining the location of interest) is called target tracking. At present, most methods simplify the expression of the tracked object, usually using rectangles and ellipses [6]. However, in order to reflect some specific characteristics of the tracked target, the results often give different manifestations, such as the center parameter of the target, the contour state of the target, and some characteristics of the target. In contrast, in accurate target contour representation instead of simplified positioning information, its precise target contour positioning not only provides the position information of the target, but also provides a basis for the subsequent behavior analysis of the target, especially the nonrigid target [7, 8].

In order to adapt to the long-term positioning of athletes and improve the positioning accuracy of athletes, this paper proposes a fusion stadium positioning tracking algorithm based on self-optimizing particle filter. Specifically, the technical contributions of this article can be summarized as follows:

First: Aiming at the initial absolute position required by the entire positioning algorithm, a seamless switching algorithm outside the stadium is proposed. For athletes entering the stadium from outdoors, the GPS feature of satellites is used to determine the switching point as the initial absolute position.

Second: This article explains that the particle filter will inevitably have the problem of lack of particle diversity after long-term resampling. In order to avoid the problem that particles cannot approach the real position of athletes well, this paper proposes a self-optimizing particle filter method.

Third: This article uses self-optimized particle filter integrated seamless switching outside the stadium or Wi-Fi static determination of the initial absolute position of the athletes, the motion equation established by the dead reckoning module of the athletes, and the observation model established by the WiFi position fingerprint module to fully approximate the position of the athletes in the stadium.

Fourth: The results show that the optimized particle filter hybrid tracking algorithm has a better tracking effect on fixed-size targets and has a certain degree of robustness to the situation where the target is partially occluded. When the size of the target changes, the fixed tracking window can still accurately represent the template information of the target, achieving a satisfactory tracking effect.

2. Related Work

Various algorithms for image processing are constantly being proposed, and with the efforts of many generations of

scientists and researchers, a leap from theory to practice has been achieved [9]. Especially in recent years, visual tracking technology has been greatly developed. It is used in military operations and surveillance, space exploration, traffic management, disease diagnosis, behavior analysis and understanding, virtual reality, video surveillance, and video compression [10]. In the research of target tracking, many problems will arise, such as the color complexity of the target and its own rotation transformation, the target is partially or completely occluded, the nonrigid performance of the object changes, the position changes drastically, and the background environment is complex [11, 12]. The target and the background are more similar, and many scholars have proposed many better algorithms to overcome this difficulty in these years [13, 14].

The University of Edinburgh in the UK used video tracking technology to develop the BEHAVE system for abnormal behavior detection. A more successful case of video tracking technology is the Kinect somatosensory system, which was developed by Microsoft in 2010 and is a somatosensory game used to distinguish human movements and sounds [15]. Sony showcased the leading application of Sony's latest 4k technology in the video security industry at the China International Public Security Products Expo, providing clearer and smarter video security solutions that can be applied to coastal prevention [16]. The German Bosch Group developed the first-generation Bosch Traffic Congestion Assist System, which was mass-produced in 2014. Sensors in front and behind the vehicle detect and track obstacles in front of the vehicle and make the vehicle make corresponding judgments through judgment. In view of the traffic conditions where vehicles frequently start and stop, the automatic driving judgment technology greatly reduces the driving intensity when traffic is congested and plays a more important role in alleviating traffic [17].

The target template is roughly a model formed by spatial geometry, and the tracking performed by this method is transformed into a process of matching the template with the features of the video sequence. For example, the most classic cardboard man model is described by plane area blocks. The movement of cardboard man often directly affects the changes of related parameters; related scholars use the time-space slice method to track the athlete's body [18]. The biggest feature of this tracking method is that the accuracy of the geometric model of the target determines the accuracy of the tracker [19]. Since the template is a simple geometric movement, it can be applied to rigid targets, and nonrigid tracking often leads to failure [20].

In recent years, because the technology of multifeature fusion is more accurate than extracting a single feature and can overcome some common difficulties, it has been studied by more and more people. The main difference between different fusion algorithms lies in the different combinations of selected features and the different algorithms for fusing these features. In order to extract accurately from the background, some scholars choose the target color and edge feature to calculate [21]. However, this method has a certain measurement significance for the feature tracking effect, but it is not comprehensive to use this as a feature fusion

calculation. Researchers merge many features (such as color, texture, and edge), which can automatically update the feature fusion coefficient, but when the appearance of the target changes, the extracted features will also change dramatically, which brings trouble to the tracking requirements [22]. Related scholars have proposed local binary texture feature description operators in feature tracking to be used for texture classification and target detection. Relevant scholars use the color and local binary texture features of the target to propose a feature fusion algorithm that can adaptively distinguish the similarity between the target and the background; however, the algorithm cannot handle the occlusion problem well, so it needs to be combined with the antiocclusion algorithm [23].

3. Multistrategy Combined Tracking Technology for Moving Targets

3.1. Multistrategy Portfolio Tracking Technology. Tracking based on target clumps is only applicable to the situation where each target moves independently [24, 25]. At this time, there is a one-to-one correspondence between the target clumps and the foreground detection clumps. When the targets are crossed and occluded, the target clumps and the foreground detection clumps will appear many-to-one. At this time, tracking based on the target clumps alone cannot meet the requirements. When the original cross-running target is separated, the target clump and the foreground detection clump will appear one-to-many, and the tracking based on the target clump also cannot meet the requirements [26–28]. Since the target clump has been extracted, the area of the clump and the circumscribed rectangular frame can be obtained, and the corner points within the target clump can also be extracted. In this paper, the area of the clump and the circumscribed rectangular frame are regarded as the characteristics of the clump. Therefore, when there is a one-to-many situation, the best foreground cluster can be selected according to the feature matching of the cluster to achieve target-based feature tracking [29, 30]. For the unmatched prospect group, a new tracking task is created. When there is a many-to-one situation, the target-based corner tracking is realized according to the corner matching in the clump. Therefore, this paper proposes a target tracking strategy that combines target clump tracking, target feature tracking, target corner tracking, and Kalman filter prediction, as shown in Figure 1. This tracking strategy can basically meet the tracking requirements of complex scenarios.

3.2. Tracking Technology Based on Target Clumps. When the detected foreground group does not have any real target group or potential target group corresponding to it, it can be considered that the foreground group corresponds to a new moving target entering the scene, and the foreground group is added to the potential target queue. Since the presence of noise can cause very short tracking, this article only shows a target that has been tracked continuously for several frames. When the number of frames successfully tracked by a

potential target group exceeds the set threshold, it is considered as a real target, displayed and added to the real target team list, and the target group is deleted from the potential target team list. The formula for judging whether the real target group or the potential target group overlaps with the detection group is as follows:

$$\begin{aligned} |x_t - x_c| &\leq \frac{w_t + w_c}{w_t - w_c}, \\ |y_t - y_c| &\leq \frac{h_t + h_c}{h_t - h_c}. \end{aligned} \quad (1)$$

Among them, the coordinates of the center point of the circumscribed rectangle of the real target group or the potential target group are (x_t, y_t) , and the width and length of the circumscribed rectangle of the real target group or the potential target group are w_t and h_t , respectively. The coordinates of the center point of the circumscribed rectangle of the foreground detection group are (x_c, y_c) , and the width and length of the circumscribed rectangle of the detection group are w_c and h_c , respectively.

When the detection group has a one-to-one correspondence with the real target group or the potential target group, it means that there is no crossover or separation between the groups. At this time, it is necessary to bring the position information of the foreground detection group into Kalman's correction equation to obtain the optimal estimated position of the target at this time. Then, the optimal position is used to update the position information of the target clump.

3.3. Tracking Technology Based on Target Features. When the real target group or the potential target group corresponds to the detection group one-to-one, the tracking method based on the target group can meet the tracking requirement. However, when the original cross-moving targets are separated, the target clumps and the foreground detection clumps have a one-to-many relationship. At this time, the tracking based on the target clump will lose its effect, because the target clump and multiple foreground detection cliques cross.

When this happens, the method used in this paper is based on the feature matching of target clumps for tracking. The characteristics of the target clump include the area of the clump and the circumscribed rectangle of the clump. The formula for target feature matching is as follows:

$$\begin{aligned} s_1 &= \int_0^1 |A_d - A_t|^{-(1/2)} dt, \\ s_2 &= \int_0^1 (|\text{rect}_h - r_h| - |\text{rect}_w + r_w|) dt, \\ s &= \frac{w_1 \cdot s_1 + w_2 \cdot s_2}{w_1 \cdot s_1 - w_2 \cdot s_2}. \end{aligned} \quad (2)$$

Among them, A_t represents the area of real target clumps or potential target clumps, A_d represents the area of foreground detection clumps, rect_w represents the width of the

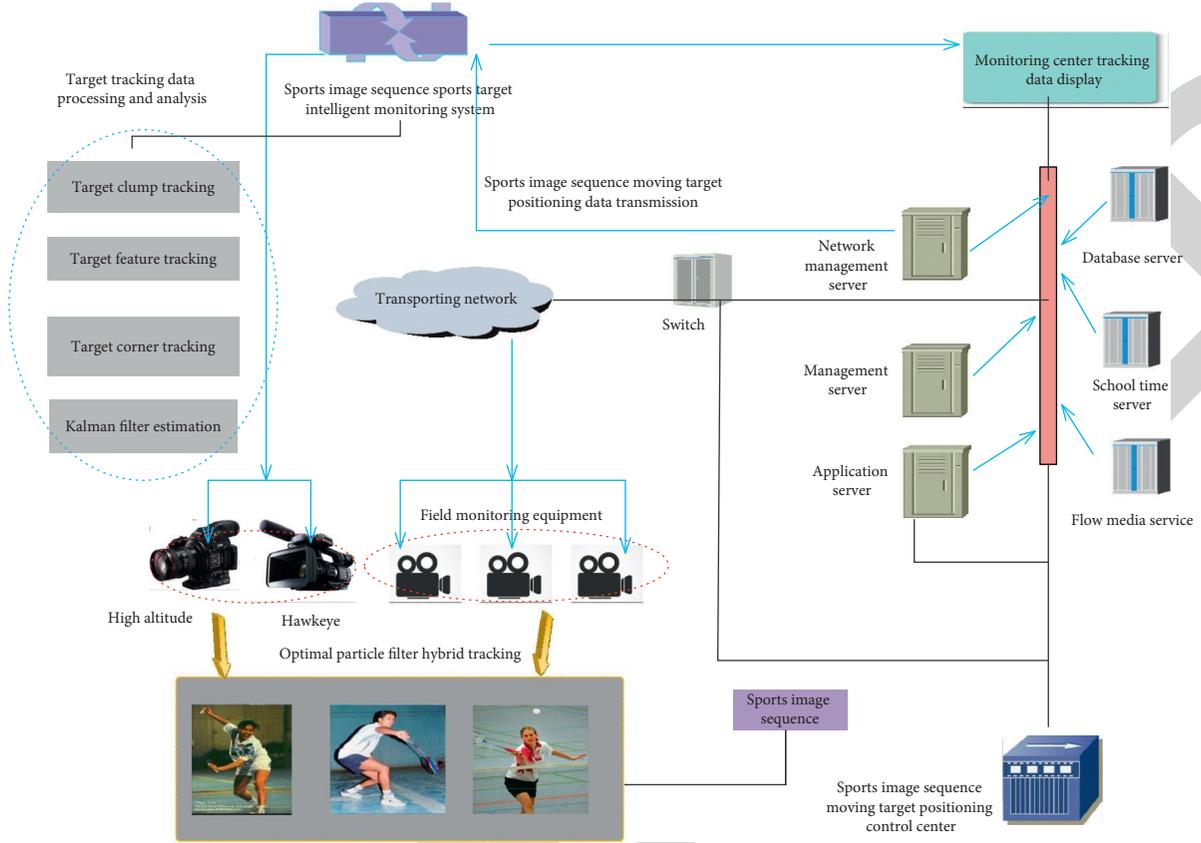


FIGURE 1: Schematic diagram of multistrategy portfolio tracking.

bounding rectangle of the real target clumps or potential target clumps, and $rect_h$ represents the real target clumps or potential targets, r_w represents the width of the circumscribed rectangle of the foreground detection blob, and r_h represents the height of the circumscribed rectangle of the foreground detection blob. W_1 and w_2 represent the weight coefficients. After many experiments, the values chosen in this paper are 0.4 and 0.6, respectively. We use the matching formula to calculate the matching score s and find the smallest matching score; then this match can be considered as the best match. Then we use the foreground to detect the location of the clump and the clump feature to update the target clump. For the prospect detection groups that failed to match, a new tracking task is started.

4. Self-Optimizing Particle Filter Fusion Tracking Algorithm

4.1. Fusion Algorithm Framework. This section presents the whole structure framework of the fusion stadium location tracking algorithm based on self-optimizing particle filter, as shown in Figure 2. The whole algorithm mainly includes three modules: WiFi position fingerprint module, athlete dead reckoning module, and self-optimizing particle filter module.

The WiFi location fingerprint module introduces the RSS rank fingerprint algorithm for signal fading and multipath effects caused by the harsh stadium environment and

the differences between different terminals and uses the characteristics of RSS rank vectors for similarity measurement, initially narrowing the positioning range, and finding several similar areas. Then, the Bayesian matching algorithm is used to confirm the position of these areas with high accuracy. At the same time, to solve the problem of signal fluctuation and the fingerprint database not being updated in time, the motion prediction method is introduced to explore the rationality of the Bayesian matching algorithm estimation result and make certain correction.

Athlete's dead reckoning module analyzes the changes of the accelerometer's signal graph for the athlete's gait not only with their own height and weight, but also with the influence of the environment. The self-learning method improves the threshold detection step in real time, analyzes the step status in different situations, and uses it. The improved integrated step length estimation algorithm calculates the step length and at the same time estimates the forward direction of the athlete based on the signal from the gyroscope.

Finally, the self-optimized particle filter module shows a lack of particle diversity over time and cannot better integrate the athlete's dead reckoning with WiFi. The self-optimized particle filter is introduced, and the degradation is judged according to the degradation coefficient before resampling. After the degree, the particles with higher weights are retained, and the characteristics of the posterior probability density distribution provided by the particles

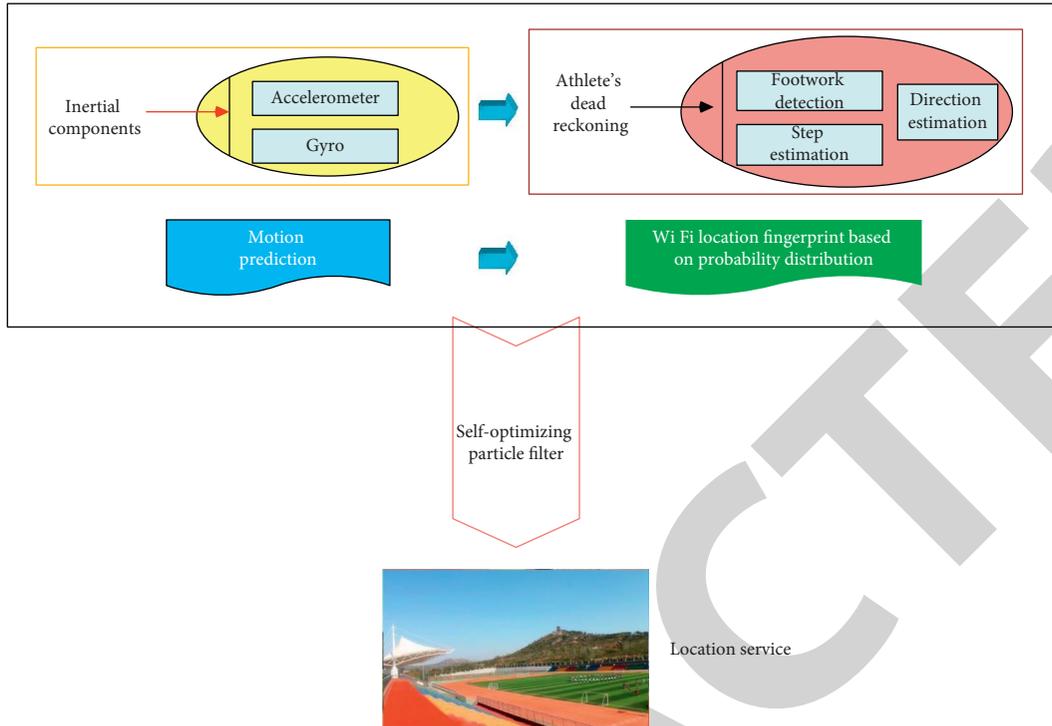


FIGURE 2: Framework diagram of stadium location tracking algorithm based on self-optimizing particle filter.

with lower weights are added when replicating the particles with higher weights, which improves the diversity of the particle set. Therefore, the motion equation established by the dead reckoning module of the athletes and the observation equation established by the WiFi position fingerprint module are combined with seamless switching outside the stadium or WiFi static determination of the initial absolute position, substituted into the stadium state space model.

4.2. Switching Method Based on Signal-to-Noise Ratio.

The signal-to-noise ratio of GPS begins to decrease rapidly near the entrance of a sports stadium. After athletes enter the sports field, the signal-to-noise ratio will drop significantly. However, the exact location of the entrance cannot be determined by using a fixed value of the average signal-to-noise ratio as the threshold, because the degree of reduction of the signal-to-noise ratio of different satellites is different, which mainly depends on the surrounding environment of the sports stadium and the position of the GPS satellite. Therefore, a switching method is proposed, which accurately switches by observing the changes in the signal-to-noise ratio of a specific satellite, instead of using a fixed value of the signal-to-noise ratio as the threshold. First, we select some GPS satellites and predict that they will show significant changes in the signal-to-noise ratio near the entrance to the sports stadium. Then, we determine the best time to perform handover by observing the change in the signal-to-noise ratio of the selected satellite.

In preliminary experiments, it can be seen that GPS satellites show significant signal-to-noise ratio changes near the entrance of the sports stadium, and these satellites are at

high altitudes. For this reason, the GPS data of athletes entering the sports field for 30 times are sampled here, and their signal-to-noise ratio changes are analyzed according to the altitude of the satellite. In the change curve of the signal-to-noise ratio of satellites with elevation angles of 30 to 90°, when the athlete is at the entrance, it indicates that the signal-to-noise ratio changes suddenly and dramatically near the vertical line. The signal-to-noise ratio curve of satellites at an elevation angle of 0 to 30° shows that there is no obvious downward trend in the signal-to-noise ratio near the vertical line. This is mainly because signals from satellites at high elevation angles are easily blocked by sports fields, while signals from satellites at low elevation angles can penetrate the sports fields through the entrance. The schematic diagram of sports target positioning is shown in Figure 3.

This algorithm fully illustrates the whole process of determining the switching point by observing the signal-to-noise ratio of the selected satellite. Continuously record the change of the signal-to-noise ratio until it reaches the position where the GPS signal cannot be received in the sports field. Then, the position where the greatest change in the signal-to-noise ratio is observed is determined as the switching point. Therefore, this algorithm can be combined with the stadium WiFi fingerprint algorithm to accurately find the initial absolute position of the stadium positioning.

4.3. Self-Optimizing Particle Filter Fusion Positioning

4.3.1. *Particle Filter Problem.* Although the unscented Kalman filter is better than the extended Kalman filter in terms of estimation accuracy and robustness and the amount

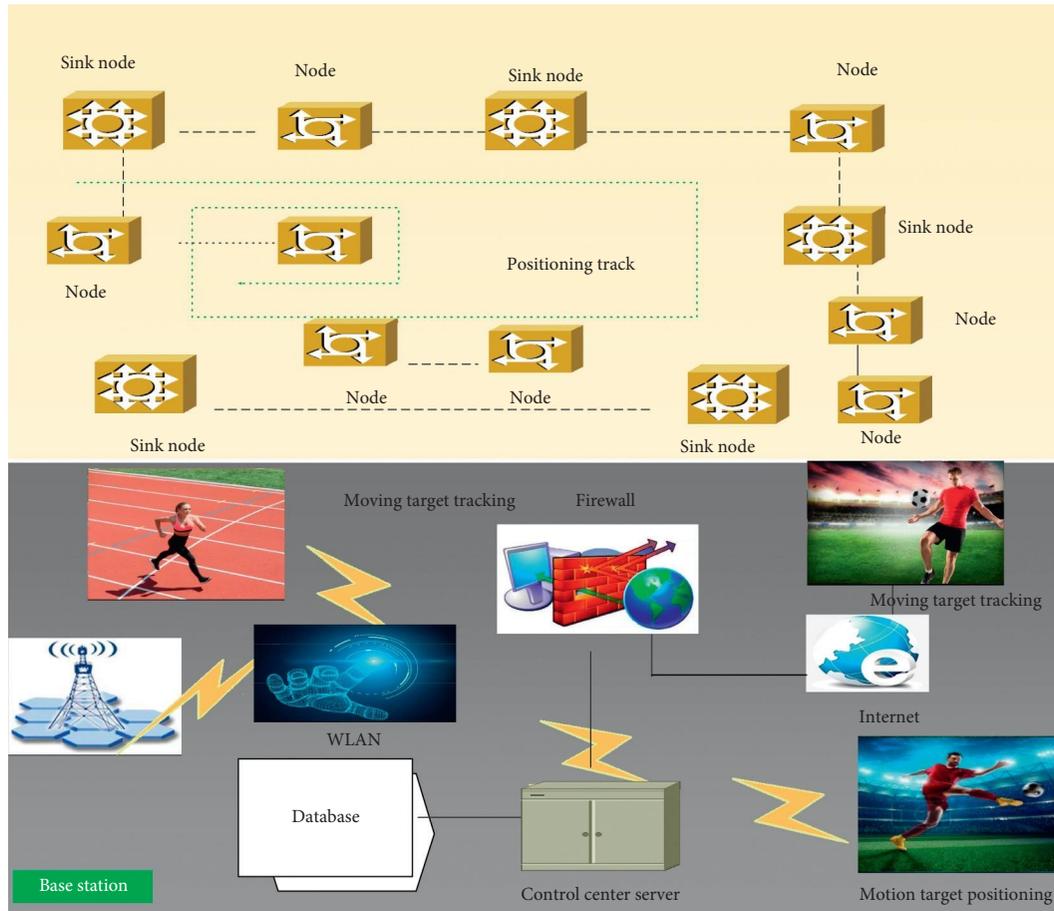


FIGURE 3: Schematic diagram of sports goal positioning.

of calculation is about the same, the unscented Kalman filter and the extended Kalman filter are both based on the Gaussian state space. Many practical problems are nonlinear, non-Gaussian, and nonstationary. The Gaussian approximation has not been able to accurately represent the true state distribution. In order to solve the above problems, the optimal estimation theory based on Monte Carlo sampling and Bayesian filtering is applied to particle filtering. In the filtering process, each sample can represent a possible state of the system, and a set of weighted samples is used to approximate the real state, and the optimal solution of the real state is obtained. It will not be constrained by the Gaussian and linear assumptions of the model and is applicable to any non-Gaussian, nonlinear dynamic space.

Particle filtering is to use a set of weighted random samples (particles) in the state space to approximate the posterior probability distribution of state variables. The core idea of particle filtering is random sampling and importance resampling. If you do not know where the athlete is at first, then randomly disperse the particles. Then, the importance of each particle is calculated according to the similarity of the features, and more particles are concentrated in the areas where the importance of the area around the athlete is strong. However, particle filtering relies heavily on the estimation of the initial state and may converge quickly or

diverge quickly. This paper also uses GPS seamless docking to determine the position of the initial state to solve this problem. However, the resampling method to solve the particle degradation problem (retaining the particles with high weights and copying them according to the value of the weight, discarding the particles with low weights) will inevitably cause the particles with high weights to be kept constant over time. Particles with low weight are copied less or even not directly discarded by copying, which will cause new problems, the lack of particle diversity. The diversity of the particle set is greatly reduced, even from the same particle or from a very small number of particles with higher weights, and it is basically impossible to approximate the posterior probability density. Therefore, a self-optimizing particle filter method is proposed to solve the problem of particle scarcity, which can better improve the accuracy of the fusion stadium positioning technology.

4.3.2. Particle Filtering Based on Monte Carlo. The core idea of particle filtering is random sampling and importance resampling. Sample importance sampling (SIR) is an importance sampling technique in Monte Carlo. In the process of collecting samples, if the target probability distribution function $p(x)$ is difficult to sample, you can select a

probability distribution $q(x)$ similar to the target probability distribution function and easy to sample for sampling, so the mathematical expectation of solving $f(x_k)$ is

$$E[f(x_k)] = \int f(x_k) p(x_k | y_1^k) dx_k. \quad (3)$$

To facilitate sampling, we use the assumed importance distribution instead of the nonlinear distribution:

$$E[f(x_k)] = \int f(x_k) q(x_k | y_1^k) \frac{p(x_k | y_1^k)}{q(x_k | y_1^k)} dx_k. \quad (4)$$

The probability formula is

$$p(x_k | y_1^k) = \frac{p(x_k) p(y_1^k | x_k)}{p(y_1^k)}. \quad (5)$$

Sampling the probability distribution with N samples uses the sample to discretize and replace the complex integration operation. This probability distribution can be called the importance function. The state x_{k+1} can sample a set of particles with weights from the importance function. The optimal estimation of the state is obtained through the nonlinear transformation of $f(x_k)$ by the particle set. However, when calculating weights, taking into account the observed values y_1^k at all times in the past, heavy calculations and huge storage space are needed to perform effective calculations. Sequential Importance Sampling (SIS) is produced in response to this difficulty. SIS considers that the state data and the observation data are relatively independent. It can be considered that the state quantity has Markov characteristics, and y_k is only related to the current state x_k .

The resampling algorithm solves the problem of particle degradation caused by sequential importance sampling. After filtering for a period of time, the weights of the particles are obviously polarized. Only a few particles have relatively large weights, and most of the other particles have very small weights or even tend to zero. Basically, they have no effect on approaching the importance distribution, but a huge amount of calculation was wasted. For the particle degradation phenomenon caused by this sequential importance sampling, a threshold is needed to define the degree of degradation to facilitate subsequent resampling. Therefore, a degradation coefficient is introduced:

$$N_{\text{eff}} = e^{\sum_{i=0}^{N-1} (w_i^k)^2}. \quad (6)$$

When the value of the coefficient is smaller, the particle degenerates more severely, so a threshold must be set. When the degradation coefficient is less than the threshold, it is determined that the particle is degraded and resampling is performed.

4.3.3. Fusion Positioning. While resampling solves the particle degradation problem, it also brings a huge new problem; that is, the particles are exhausted after multiple resampling, and the particles with higher weight are retained multiple times. The resampling result contains many

repeated particles, which is relatively characterizable. The particles of the posterior probability density distribution are gradually discarded in the resampling process, which seriously loses the diversity of the particles. Therefore, a resampling algorithm is designed to overcome the lack of particles. Before resampling, after judging the degree of degradation according to the degradation coefficient, the particles with higher weights are retained, and the particles with lower weights are added when the particles with higher weights are copied. The characteristics provided by the posterior probability density distribution increase the diversity of particle collections and overcome the problem of particle shortage. First, we establish a state space model for the positioning and tracking of stadium athletes. In the above calculation of the dead reckoning of athletes, the step length estimated by the accelerometer and the angle estimated by the gyroscope are established to establish the system motion model:

$$\begin{cases} x_k = S_k \sum_{i=1}^k (x_i, u_i), \\ \begin{cases} a_{k+1} = a_k - l_k \sin \theta_k, \\ b_{k+1} = b_k - l_k \cos \theta_k. \end{cases} \end{cases} \quad (7)$$

Among them, (a_k, b_k) is the position of the athlete at time k , l_k is the athlete's step length at time k , θ_k is the angle at time k , and the ambient noise in l_k and θ_k obeys the normal distribution $N(0, \sigma_{s_2})$.

When the resampling step continues over time, particles with lower weights are continuously discarded, and the characteristic of posterior probability density basically comes from a small number of particles with higher weights, and the particle diversity is greatly reduced. This paper changes the resampling process to completely abandon the low-weight particles but embeds the posterior probability density characteristics that the low-weight particles can represent into the copied particles with higher weights.

The motion model is established by the dead reckoning algorithm based on inertial sensors, the observation model is established by the stadium positioning algorithm based on WiFi location fingerprint, and the location fingerprint based on Bayesian algorithm is used to replace the sample mean value with probability distribution to analyze the particles more accurately. We directly use the position fingerprint information to update the particle weights and use self-optimizing particle filtering to approximate the posterior probability distribution, to solve the problem of the gradual decrease of particle diversity in the continuous resampling process, and to retain the weight of particles with lower weights during the resampling process.

5. Simulation Experiment and Result Analysis

5.1. Experimental Image Sequence S1. The sequence processed in the experiment has a total of 200 frames, the frame height and frame width are 288 and 512, respectively, the data rate is 3346 kpbs, the total bit rate is 3346 kpbs, and the frame rate is 31 frames per second. The tracked movement target is a badminton player, and the movement direction of

the target always changes dynamically during the whole tracking process. The experimental sequence S1 selects the number of image frames in the video as 20, 40, 60, and 80 and uses the optimized particle filter hybrid tracking algorithm to perform tracking experiments on the moving targets in the sequence. In the initial frame of the video, manually we select the scale and position coordinates of the rectangular tracking window and use this as the initial position of the iteration. The tracking results of this experiment are shown in Figure 4.

According to the processing results of the image sequence S1, it can be seen that when the background is relatively simple and the target is not occluded, the optimized particle filter hybrid tracking algorithm has better tracking results. Although the tracking window of individual frames such as the 20th frame and the 40th frame has a slight offset, the optimal position can be quickly found by Mean Shift iteration. In the subsequent image frames, the tracking window is always kept around the center of the moving target to achieve accurate tracking of the target. Under the optimized particle filter hybrid tracking algorithm, the distribution of the Bhattacharyya coefficient with the image frame is shown in Figure 5.

5.2. Experimental Image Sequence S2. This video sequence has a total of 200 frames, the frame height and frame width are 240 and 360, respectively, the data rate is 32922 kpbs, the total bit rate is 32922 kpbs, and the frame rate is 15 frames per second. The moving target being tracked is a moving target, and the moving direction of the target is from left to right relative to the camera position during the whole tracking process. The target encounters partial occlusion from the 16th frame, but it is not completely occluded during the experiment. The experimental sequence S2 selects the number of image frames in the video as 15, 30, 45, and 60. Similar to the process of sequence S1, the optimized particle filter hybrid tracking algorithm is used to perform tracking experiments on the moving targets in the sequence. In the initial frame of the video, manually we select the scale and position coordinates of the rectangular tracking window and use this as the initial position of the Mean Shift iteration. The tracking result is shown in Figure 6.

According to the processing results of the image sequence S2, it can be seen that the conventional Mean Shift algorithm has certain robustness when the target encounters partial (slight) occlusion. Around the 20th frame, the tracked vehicle drove into the bush area, the target was partially occluded, and the upper part of the vehicle was exposed in the field of view; at the 37th frame, the occlusion phenomenon was aggravated, and the tracking window can still accurately track the target at this time. From the 37th frame to the 50th frame, the occluded part of the tracked vehicle changes. Because the Mean Shift algorithm is robust to the target tracking under partial occlusion, it can be seen that the tracking effect is still relatively ideal. It can be seen from the 70th frame that when the vehicle drives out of the bush area,

the tracking window accurately locates the target again. The distribution of the Bhattacharyya coefficient with the image frame under sequence S2 is shown in Figure 7. Combining the above tracking process, it can be seen that, between the 40th frame and the 60th frame, the accuracy of the target template is reduced due to the larger part of the target being occluded, and the Bhattacharyya coefficient reaches a relatively low value. The occlusion phenomenon gradually improved from left to right, so the value of this coefficient showed an upward trend.

5.3. Experimental Image Sequence S3. This video sequence has a total of 200 frames, the frame height and frame width are 240 and 360, respectively, the data rate is 1079 kpbs, the total bit rate is 1079 kpbs, and the frame rate is 15 frames per second. The moving target to be tracked is the athlete in front of the wall. The moving direction of the target is from right to left relative to the camera position during the whole tracking process. The distance from the camera is gradually reduced, and the target size is increasing. The experimental sequence S3 selects the number of image frames in the video as 25, 50, 75, and 100. The conventional Mean Shift algorithm is used to track the moving targets in the sequence, which is similar to the processing process of the sequences S1 and S2. The frame needs to manually select the scale and position coordinates of the tracking window and use this as the initial position of the Mean Shift iteration. The tracking result is shown in Figure 8.

According to the processing results of the image sequence S3, it is not difficult to see that, for the tracking of moving targets with varying sizes, the optimized particle filter hybrid tracking algorithm has an ideal tracking effect. The rectangular tracking window is manually selected in the initial frame. The size of the target is constantly changing, but the size of the tracking window cannot be adjusted automatically. During the tracking process from frame 45 to frame 57, the tracking window has begun to lose part of the target area. Since the scale of the target has been changing during the tracking process, and the tracking window has not changed accordingly, it is unreasonable to use the initial tracking window to establish a target template. The distribution of the Bhattacharyya coefficient with the image frame under sequence S3 is shown in Figure 9.

For the above three image sequences, after many simulation experiments, the execution efficiency of the Mean Shift target tracking algorithm based on the kernel histogram is calculated, that is, the average number of single-frame iterations and single-frame execution time. The results are shown in Figure 10. Since the background in sequence S1 is relatively simple and the scale of the target is basically unchanged, the number of iterations for a single frame is less than that of the other two sequences. However, because the target area in sequence S3 is larger and more pixels are involved in the calculation of the kernel histogram, the average single-frame execution time of the algorithm is longer than that of the other two sequences.

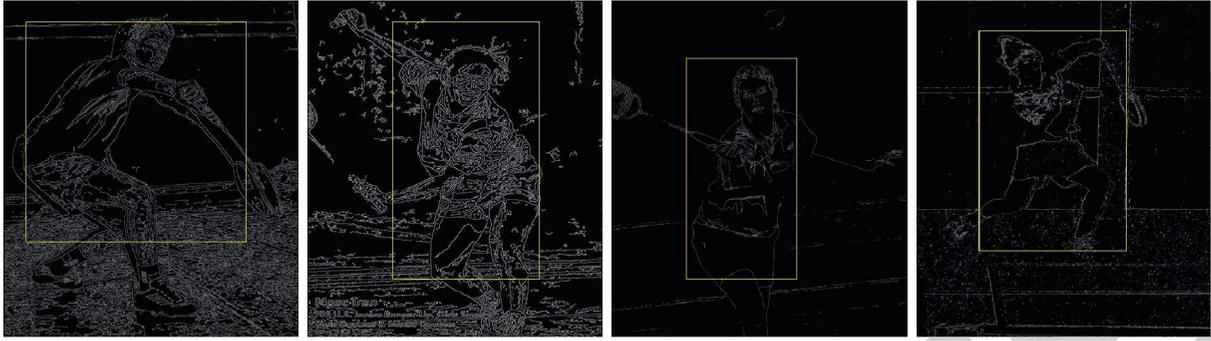


FIGURE 4: The tracking results of the experimental image sequence S1.

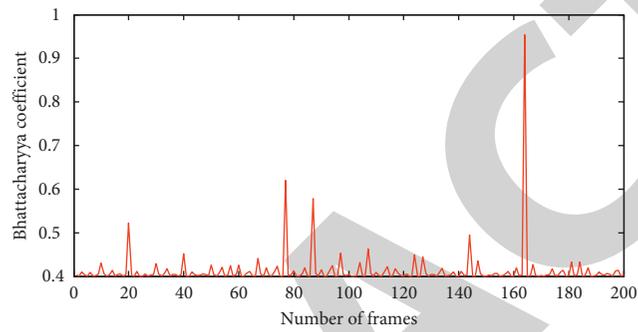


FIGURE 5: The distribution of the Bhattacharyya coefficient in the experimental image sequence S1 with respect to the number of frames.

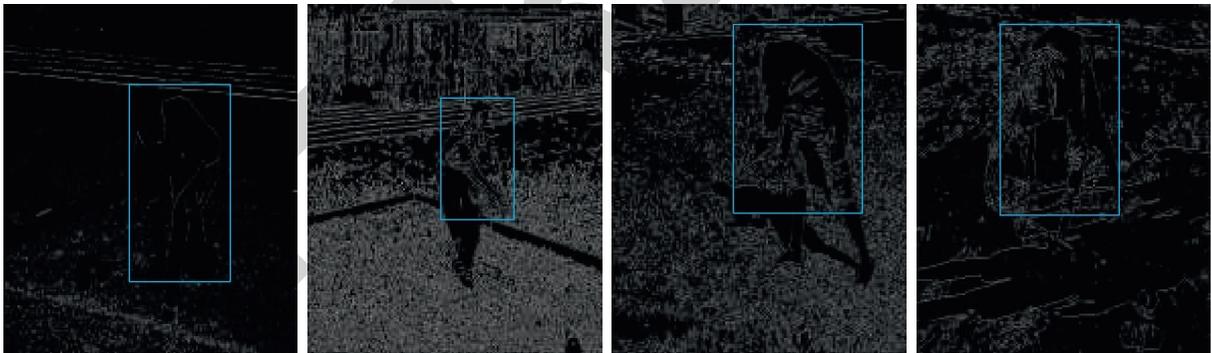


FIGURE 6: Tracking results of experimental image sequence S2.

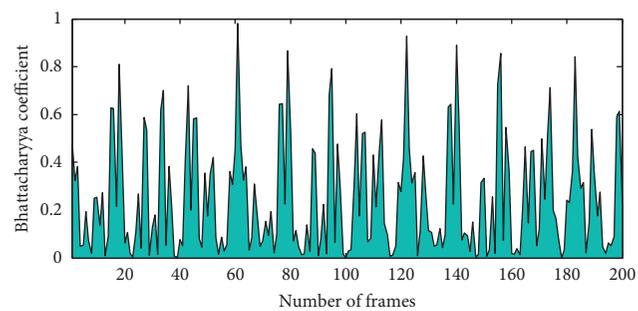


FIGURE 7: The distribution of the Bhattacharyya coefficient in the experimental image sequence S2 with respect to the number of frames.



FIGURE 8: Tracking results of experimental image sequence S3.

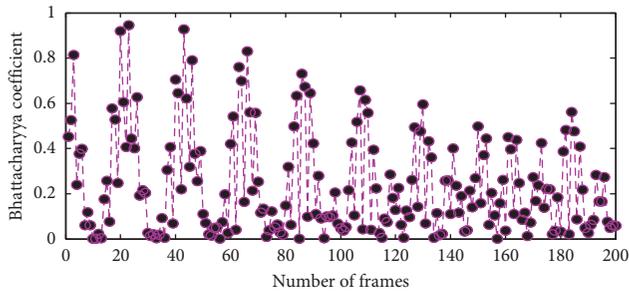


FIGURE 9: The distribution of the Bhattacharyya coefficient in the experimental image sequence S3 with respect to the number of frames.

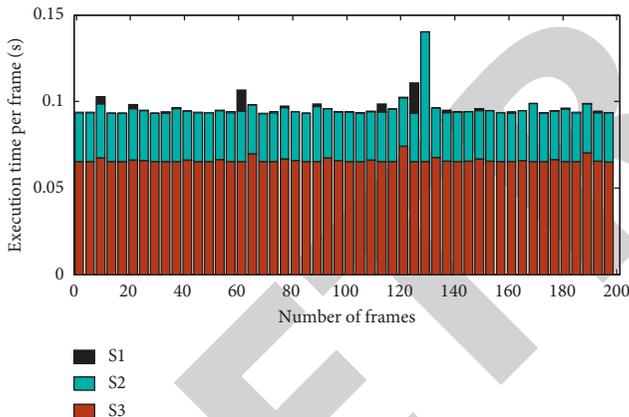


FIGURE 10: Execution time of the experimental sequence.

6. Conclusion

In this paper, self-optimizing particle filter is used to fusion tracking and positioning of the improved dead reckoning of athletes and WiFi position fingerprint algorithm. First of all, it is necessary to determine the initial absolute position of the entire stadium positioning algorithm. For athletes entering the stadium from the outside, a seamless switching algorithm outside the stadium is proposed. With the characteristics of high-altitude satellite GPS, a suitable switching point is found as the initial absolute position. We determine the initial absolute position. Then, aiming at the problem that the poorly diversified particles cannot be better integrated and localized, a self-optimized particle filter method is proposed. After resampling and retaining high-weight particles, the characteristics of low-weight particles are embedded in the copied high-weight particles. Since the

video is composed of many consecutive frames of images, the target tracking process based on the image sequence is to find the target area in each frame of image. First, a kernel function needs to be superimposed in this area, assuming that this function is isotropic. Using this kernel function to weight the color feature points in the area, the weight near the center position is the highest, and the weight is decreasing from the center to the edge position, thereby generating a kernel histogram to represent the target. The process of finding the target is the process of matching the kernel histogram. The similarity judgment between the two regions is completed by the similarity measurement function. This function must have smoothness in order to create conditions for the gradient estimation method. The abovementioned target area search method is much faster than the general method, so it can realize the rapid target positioning. Simulation verification and result analysis of the algorithm prove that the algorithm has better tracking results for sports targets.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] Q.-b. Zhang, P. Wang, and Z.-h. Chen, "An improved particle filter for mobile robot localization based on particle swarm optimization," *Expert Systems with Applications*, vol. 135, pp. 181–193, 2019.
- [2] N. Xu, Y. Zhang, and D. Zhang, "Moving target tracking in three dimensional space with wireless sensor network," *Wireless Personal Communications*, vol. 94, no. 4, pp. 3403–3413, 2017.
- [3] Z. Zhou, M. Zhou, and J. Li, "Object tracking method based on hybrid particle filter and sparse representation," *Multimedia Tools and Applications*, vol. 76, no. 2, pp. 2979–2993, 2017.
- [4] I. Ullah, Y. Shen, X. Su et al., "A localization based on unscented Kalman filter and particle filter localization algorithms," *IEEE Access*, vol. 8, pp. 2233–2246, 2019.
- [5] M. Firouznia, K. Faez, H. Amindavar et al., "Chaotic particle filter for visual object tracking," *Journal of Visual Communication and Image Representation*, vol. 53, pp. 1–12, 2018.

- [6] R. Havangi, "Target tracking based on improved unscented particle filter with Markov chain Monte Carlo," *IETE Journal of Research*, vol. 64, no. 6, pp. 873–885, 2018.
- [7] Y. Xiao and D. Pan, "Research on robust visual tracker based on multi-cue correlation particle filters," *IEEE Access*, vol. 8, pp. 19555–19563, 2020.
- [8] N. Xia and M. A. Weitnauer, "TDOA-based mobile localization using particle filter with multiple motion and channel models," *IEEE Access*, vol. 7, pp. 21057–21066, 2019.
- [9] F. Song, M. Zhu, Y. Zhou et al., "Smart collaborative tracking for ubiquitous power IoT in edge-cloud interplay domain," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6046–6055, 2019.
- [10] H. Nenavath and R. K. Jatoth, "Hybrid SCA-TLBO: a novel optimization algorithm for global optimization and visual tracking," *Neural Computing and Applications*, vol. 31, no. 9, pp. 5497–5526, 2019.
- [11] Z. Pan, S. Liu, and W. Fu, "A review of visual moving target tracking," *Multimedia Tools and Applications*, vol. 76, no. 16, pp. 16989–17018, 2017.
- [12] F. Sardari and M. E. Moghaddam, "A hybrid occlusion free object tracking method using particle filter and modified galaxy based search meta-heuristic algorithm," *Applied Soft Computing*, vol. 50, pp. 280–299, 2017.
- [13] C. Wang, J. Luo, and Y. Zheng, "Optimal target tracking based on dynamic fingerprint in indoor wireless network," *IEEE Access*, vol. 6, pp. 77226–77239, 2018.
- [14] M. C. Chen, S. Q. Lu, and Q. L. Liu, "Uniqueness of weak solutions to a Keller-Segel-Navier-Stokes model with a logistic source," *Applications of Mathematics*, 2021.
- [15] S. Tomic, M. Beko, R. Dinis et al., "Bayesian methodology for target tracking using combined RSS and AoA measurements," *Physical Communication*, vol. 25, pp. 158–166, 2017.
- [16] J. M. Pak, P. S. Kim, S. H. You et al., "Extended least square unbiased FIR filter for target tracking using the constant velocity motion model," *International Journal of Control, Automation and Systems*, vol. 15, no. 2, pp. 947–951, 2017.
- [17] Z. Zhao, P. Feng, J. Guo et al., "A hybrid tracking framework based on kernel correlation filtering and particle filtering," *Neurocomputing*, vol. 297, pp. 40–49, 2018.
- [18] Y. He, B. Liang, J. He et al., "Non-cooperative spacecraft pose tracking based on point cloud feature," *Acta Astronautica*, vol. 139, pp. 213–221, 2017.
- [19] C. Hu, Z. Zhang, Y. Tao et al., "Decentralized real-time estimation and tracking for unknown ground moving target using UAVs," *IEEE Access*, vol. 7, pp. 1808–1817, 2018.
- [20] N. Zeng, Z. Wang, H. Zhang et al., "An improved particle filter with a novel hybrid proposal distribution for quantitative analysis of gold immunochromatographic strips," *IEEE Transactions on Nanotechnology*, vol. 18, pp. 819–829, 2019.
- [21] Q. Tian, I. Kevin, K. Wang et al., "A resetting approach for INS and UWB sensor fusion using particle filter for pedestrian tracking," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 8, pp. 5914–5921, 2019.
- [22] S. Chakravorty, "An unscented Kalman-particle hybrid filter for space object tracking," *The Journal of the Astronautical Sciences*, vol. 65, no. 1, pp. 111–134, 2018.
- [23] P. Singh, A. Khosla, A. Kumar et al., "Computational intelligence based localization of moving target nodes using single anchor node in wireless sensor networks," *Telecommunication Systems*, vol. 69, no. 3, pp. 397–411, 2018.
- [24] J. Zhang and B. Liu, "A review on the recent developments of sequence-based protein feature extraction methods," *Current Bioinformatics*, vol. 14, no. 3, pp. 190–199, 2019.
- [25] L. Ding, S. Li, H. Gao et al., "Adaptive neural network-based finite-time online optimal tracking control of the nonlinear system with dead zone," *IEEE Transactions on Cybernetics*, vol. 51, no. 1, pp. 382–392, 2019.
- [26] B. Wang, F. C. Zou, J. Cheng et al., "Fault detection filter design for continuous-time nonlinear Markovian jump systems with mode-dependent delay and time-varying transition probabilities," *Advances in Difference Equations*, vol. 2017, no. 1, pp. 1–23, 2017.
- [27] J. Yang, C. Wang, B. Jiang et al., "Visual perception enabled industry intelligence: state of the art, challenges and prospects," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 3, pp. 2204–2219, 2020.
- [28] X. Liu, H. Song, and A. Liu, "Intelligent UAVs trajectory optimization from space-time for data collection in social networks," *IEEE Transactions on Network Science and Engineering*, 2020.
- [29] A. May, "Solving subset sum with small space-handling cryptanalytic big data," *Information Technology*, vol. 62, no. 3–4, pp. 181–187, 2020.
- [30] J. Wen, J. Yang, B. Jiang et al., "Big data driven marine environment information forecasting: a time series prediction network," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 1, pp. 4–18, 2020.