Application of Adaptive UKF Algorithm in Multi-target Tracking and Positioning System

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Abstract

Adaptive filtering algorithms are widely used in various fields, such as signal processing, control engineering, and communication systems. The Finite Impulse Response (FIR) adaptive filtering algorithm is a design method used for adaptive variable target tracking systems based on a probability density distribution model. The main goal of the FIR adaptive filtering algorithm is to track the movement of a target within a global range. To achieve this, the algorithm estimates the parameters of different regions in the image. By doing so, the algorithm can adaptively adjust its parameters to cope with the changes in the target's movement pattern. This adaptive behavior improves the algorithm's real-time performance and effectiveness in tracking the target. The FIR adaptive filtering algorithm operates by taking input signals and applying a linear filter to them. The filter coefficients are adjusted continuously in response to changes in the target's movement. This adjustment is done by minimizing the error between the estimated target position and the actual position. As the target moves, the algorithm updates its estimate and adjusts its parameters accordingly. The FIR adaptive filtering algorithm is based on a probability density distribution model. This model assumes that the input signal is a random process with an unknown probability density function. The algorithm estimates this probability density function and uses it to adjust its filter coefficients. Overall, the FIR adaptive filtering algorithm is an effective method for tracking variable targets in real-time. Its adaptive nature allows it to adjust to changes in the target's movement, making it useful in a variety of applications where tracking moving objects is necessary.

Keywords: Adaptive Filtering Algorithm, Multi-target Tracking, Positioning System

1. Introduction

Adaptive filter, specifically Support Vector Machine (SVM), is a type of passive neural network that is designed to process uncertain or noisy data. The adaptive filtering algorithm implemented in SVM is a non-minimum mean square error filter, which makes it effective in reducing noise and errors in data processing. The adaptive filtering algorithm is based on two main ideas [1-3]. Firstly, it employs the concept of regularization, which involves adding a penalty term to the objective function to prevent overfitting. Overfitting is a common problem in machine learning algorithms, where the model is too complex and learns the noise in the data instead of the underlying pattern. Regularization helps to balance the bias-variance trade-off, leading to better generalization performance.

The Adaptive Unscented Kalman Filter (UKF) algorithm is a powerful tool used in multi-target tracking and positioning systems. It is a variant of the standard Kalman filter, which is widely used in signal processing applications. The UKF algorithm is particularly useful in situations where the system dynamics are nonlinear and cannot be modeled using traditional linear models. The adaptive UKF algorithm builds on this foundation by dynamically adjusting the filter parameters to accommodate changes in the system dynamics. This makes it particularly effective in scenarios where the system is subject to sudden changes, such as in multi-target tracking applications. The adaptive UKF algorithm has been successfully applied in a range of applications, including robotics, navigation, and signal processing.

The use of the adaptive UKF algorithm in multi-target tracking and positioning systems has significant advantages over traditional tracking algorithms. It enables accurate estimation of the positions and velocities of multiple targets in real-time, even in challenging environments. The algorithm is also robust to measurement noise and uncertainties, which are common in real-world scenarios. In addition, the adaptive UKF algorithm is computationally efficient and requires relatively low processing power, making it well-suited to implementation on embedded systems. These advantages make the adaptive UKF algorithm a valuable tool in a range of applications, including radar tracking, autonomous vehicles, and surveillance systems.

Secondly, the algorithm uses a kernel function to transform the input data into a higher-dimensional space where it is easier to find a hyperplane that separates the data into classes. This approach is known as the kernel trick and is one of the key features of SVM. The kernel function can be chosen based on the nature of the data and the problem at hand, allowing the algorithm to be customized for different applications. In this paper, the adaptive filtering algorithm is applied to the problem of target tracking [1,4,5]. Specifically, the paper analyzes the limitations of the classic ant colony optimization method in locating targets and proposes a new approach based on parameter estimation using the mutual mapping relationship between feature points. This approach involves modeling the target image and using the SVM algorithm to estimate the parameters of the model. By doing so, the algorithm can track the target more accurately and efficiently, even in noisy or complex environments.

In conclusion, the adaptive filtering algorithm based on SVM is a powerful tool for processing uncertain or noisy data. Its ability to adapt to different applications and its regularization and kernel functions make it effective in reducing errors and improving generalization performance. In the context of target tracking, the algorithm can be used to improve the accuracy and efficiency of locating targets, making it useful in a variety of applications.

2. Principle and method of target tracking filtering

2.1. Discrete Kalman Filter

The Discrete Kalman Filter is a popular algorithm that is used for state estimation problems. The filter is used to estimate the state of a system based on noisy observations. The algorithm uses a mathematical model of the system and the noise characteristics to estimate the state of the system. The Discrete Kalman Filter is widely used in various fields such as robotics, control systems, navigation systems, and signal processing. The Discrete Kalman Filter is a recursive algorithm that updates the estimate of the system state based on new observations. The algorithm consists of two main steps: the prediction step and the update step [6]. In the prediction step, the algorithm predicts the next state of the system based on the current state and the system model. In the update step, the algorithm updates the estimate of the state based on the observation and the prediction error.

The Discrete Kalman Filter uses a stochastic model of the system, which includes the system dynamics and the noise characteristics. The noise in the system is assumed to be Gaussian and uncorrelated. The filter estimates the state of the system by minimizing the mean square error between the predicted and observed states. One of the advantages of the Discrete Kalman Filter is its ability to handle noisy and uncertain measurements. The filter can estimate the state of the system even when the observations are corrupted by noise. Moreover, the filter can be used to estimate the state of a system when only partial measurements are available [7-11].

The Discrete Kalman Filter has several applications in real-world problems. For example, it is used in the Global Positioning System (GPS) to estimate the position and velocity of a receiver based on satellite measurements. The filter is also used in autonomous vehicles to estimate the position and orientation of the vehicle based on sensor measurements. In conclusion, the Discrete Kalman Filter is a powerful algorithm that can be used for state estimation problems [12]. The filter uses a mathematical model of the system and the noise characteristics to estimate the state of the system. The filter is widely used in various fields such as robotics, control systems, navigation systems, and signal processing. The filter is advantageous because it can handle noisy and uncertain measurements, and it can be used to estimate the state of a system when only partial measurements are available.

In the discrete Kalman filter, the law of the target motion state changing with time is described by the state equation, and the relationship between the measurement vector and the state vector is described by the measurement equation [13]. The mathematical description in discrete linear systems has the following form:

The state equation is shown in formula (1):

$$X_k = \Phi_{k/k-1} X_{K-1} + \Gamma_{k-1} W_{k-1} \tag{1}$$

The measurement equation is shown in formula (2):

$$Z_k = H_k X_k + V_k \tag{2}$$

Discrete Kalman filter is a finite-dimensional linear discrete algorithm with a recursive structure, which is very suitable for computer implementation. Its main features:

1) The discrete Kalman filter uses the unbiased minimum variance criterion to obtain the optimal estimate of the system;
2) The signal model of the discrete Kalman filter is described by the state equation and the measurement equation. It can be applied to the state estimation of multivariable systems, time-varying systems and non-stationary random processes;
3) The state estimation of the discrete Kalman filter is calculated by using the recursive method, that is, the current value of the signal is estimated only based on the previous estimation value and the latest measurement data.Therefore, the discrete Kalman filter data storage is small, the calculation is small, and the convergence speed is fast, especially this avoids the problem of high-order matrix inversion and improves the calculation efficiency;
4) X_k and $X_{k+1/k}$ P_k and $P_{k+1/k}$ can be obtained at the same time, which are the accuracy indicators of state filtering and state one-step prediction;
5) Discrete Kalman filter has good real-time performance and noise immunity [14]. Kalman algorithm quickly became the mainstream algorithm of tracking algorithm with its excellent characteristics. Now, people have created many algorithms with better filtering performance based on the classic Kalman filter. But in the final analysis, they are all Kalman filtering algorithms. For a long time, discrete Kalman filter has been regarded as the best choice to solve problems such as target tracking and data prediction.

2.2. Extended Kalman filter algorithm

The Extended Kalman filter algorithm (EKF) is a mathematical technique used for nonlinear state estimation problems in dynamic systems. EKF is a recursive filter that estimates the state of a system given the measurements and the dynamic model of the system [15-18]. The EKF algorithm is based on the Kalman filter algorithm, but it uses a nonlinear system model and an approximation of the probability distribution of the state estimate. The EKF algorithm is widely used in various fields, including engineering, finance, and science. In engineering, EKF is used to estimate the states of nonlinear systems, such as aircraft control, satellite attitude control, and robotics. In finance, EKF is used for estimating stock prices, option prices, and portfolio returns [19]. In science, EKF is used for estimating the state of physical systems, such as weather forecasting, climate modeling, and biological systems.

The EKF algorithm involves two main steps: prediction and update. In the prediction step, the algorithm uses the system model to estimate the state of the system at the next time step. In the update step, the algorithm uses the measurements to update the state estimate [20]. The EKF algorithm uses a linearization technique to approximate the nonlinear system model and the measurement model. The linearization technique involves calculating the Jacobian matrices of the system and measurement models. These matrices are used to linearize the system and measurement models around the current state estimate. The EKF algorithm has several advantages over other nonlinear estimation techniques. First, the EKF algorithm is computationally efficient and can handle high-dimensional systems. Second, the EKF algorithm is robust to noise and measurement errors. Third, the EKF algorithm provides a measure of the uncertainty in the state estimate, which can be used for decision-making and control. However, the EKF algorithm has several limitations. First, the EKF algorithm relies on the accuracy of the linearization approximation, which may not be accurate for highly nonlinear systems. Second, the EKF algorithm is sensitive to the initial state estimate and the choice of the covariance matrix. Third, the EKF algorithm assumes Gaussian noise, which may not be true for all systems.

In conclusion, the Extended Kalman filter algorithm is a powerful technique for estimating the state of nonlinear dynamic systems. The algorithm is widely used in various fields due to its computational efficiency, robustness, and ability to estimate the uncertainty in the state estimate. However, the EKF algorithm has some limitations that should be considered when applying it to real-world problems. Overall, the EKF algorithm is a valuable tool for nonlinear state estimation problems and has many practical applications. The application of linear models in target motion is greatly restricted, because most target motions have great maneuverability [4,21-23]. The model is usually non-linear, such as high-altitude target flight trajectory measurement, trajectory tracking of water maneuvering targets studied in this paper, etc.Linearizing a nonlinear model is a basic method to solve nonlinear filtering, that is, an approximate method to describe a nonlinear system with linearization. The linearized filtering method of nonlinear filtering is expressed by a difference equation as shown in formulas (3) and (4):

$$x_k = f\,(x_{k-1}, k - 1) + W_{k-1} \tag{3}$$

$$z_k = h(x_k, k) + v_k \tag{4}$$

2.3. Insensitive Kalman filter algorithm

The Insensitive Kalman filter algorithm (IKF) is a variant of the Kalman filter that is designed to be insensitive to measurement noise [24]. Unlike the traditional Kalman filter, which assumes that the measurement noise is Gaussian, the IKF algorithm assumes that the measurement noise is heavy-tailed and can be modeled using the Cauchy distribution. The IKF algorithm is particularly useful for state estimation problems where the measurement noise is non-Gaussian and has heavy tails. The IKF algorithm was first introduced in the 1990s and has since been used in various fields, including control systems, signal processing, and finance. In control systems, the IKF algorithm is used for tracking targets, controlling unmanned aerial vehicles, and controlling robots. In signal processing, the IKF algorithm is used for image processing, audio processing, and radar processing. In finance, the IKF algorithm is used for portfolio optimization, risk management, and asset pricing [25].

The IKF algorithm involves two main steps: prediction and update. In the prediction step, the algorithm uses the system model to estimate the state of the system at the next time step. In the update step, the algorithm uses the measurements to update the state estimate. The IKF algorithm uses a non-Gaussian likelihood function to model the measurement noise. The likelihood function is based on the Cauchy distribution, which has heavy tails and can handle outliers in the measurement data. The IKF algorithm has several advantages over the traditional Kalman filter. First, the IKF algorithm is robust to measurement noise and can handle non-Gaussian measurement errors. Second, the IKF algorithm is less sensitive to outliers in the measurement data and can provide more accurate state estimates. Third, the IKF algorithm provides a measure of the uncertainty in the state estimate, which can be used for decision-making and control.

However, the IKF algorithm has some limitations that should be considered when applying it to real-world problems. First, the IKF algorithm is computationally more expensive than the traditional Kalman filter due to the non-Gaussian likelihood function. Second, the IKF algorithm may not perform well in situations where the measurement noise is not heavy-tailed. Third, the IKF algorithm may not be suitable for systems with highly nonlinear dynamics. In conclusion, the Insensitive Kalman filter algorithm is a powerful technique for state estimation problems where the measurement noise is heavy-tailed and non-Gaussian. The algorithm is robust, less sensitive to outliers, and provides a measure of uncertainty in the state estimate. However, the IKF algorithm has some limitations that should be carefully considered when applying it to real-world problems. Overall, the IKF algorithm is a valuable tool for state estimation problems in various fields and has many practical applications.

Unscented transformation is the core and foundation of the UKF algorithm. It is a new method of calculating statistical properties in nonlinear systems.The idea of UT transformation: select a set of Sigma points to make the sample mean and covariance consistent with the mean x and covariance of the state random variable, and then perform nonlinear transformation on these points to obtain Px the mean y and covariance of the transformed points .Although the sampling points are not Py obtained by random selection, this deterministic sampling method extracts state-specific statistical characteristic information [5]. Suppose that the random variable x undergoes a nonlinear transformation as shown in formula (5):

$$y = f(x) \tag{5}$$

Here x is a Gaussian random vector with mean x and variance P_X, , and the dimension is L. Then Px the statistical properties of y can be obtained by the following UT transformation [6]. A matrix x containing 2L+1 vectors Xi. Here, let be as shown in formulas (6) and (7):

$$X_0 = x, i = 0$$

$$X_i = x + (\sqrt{(L + K)P_x})i \text{ , } i = 1..., L$$

$$X_i = x + (\sqrt{(L + K)P_x}) \quad _{i-L}, L + 1,..., 2L \tag{6}$$

$$W_i = k/(L + K),\ i = 0$$

$$W_i = k/(2(L + K)),\ i = 1,..., 2L \tag{7}$$

$(\sqrt{(L + \lambda)P_x})i$ represents the i-th column vector of the square root of the matrix $(L + \lambda)P_X$ k is the scale scalar, which is used to control the distance (scale, Scaling) from each point to the mean. Wi is the weight corresponding to the Sigma point and satisfies formula (8):

$$\Sigma W_{i=1} \tag{8}$$

Then the mean and covariance of y can be calculated by formulas (9), (10), (11):

$$y_1 = f(x_{i)},\ i = 0, 1,..., 2L \tag{9}$$

$$\underline{y} = \sum_{i=0}^{2L} W_i y_i \tag{10}$$

$$P_y = \sum_{i=0}^{2L} W_i(y_i - \underline{y})(y_i - \underline{y})^T \tag{11}$$

2.4. IMM-UKF filtering algorithm

The IMM-UKF filtering algorithm is a variant of the Unscented Kalman filter (UKF) algorithm that combines multiple Kalman filters to estimate the state of a dynamic system. The Interacting Multiple Model (IMM) algorithm is used to switch between the different Kalman filters based on the system dynamics. The IMM-UKF algorithm is particularly useful for state estimation problems where the system dynamics are unknown or vary over time. The IMM-UKF algorithm was first introduced in the 1990s and has since been used in various fields, including robotics, aerospace, and navigation. In robotics, the IMM-UKF algorithm is used for mapping, localization, and control of autonomous vehicles. In aerospace, the IMM-UKF algorithm is used for spacecraft guidance, navigation, and control. In navigation, the IMM-UKF algorithm is used for GPS-denied environments and indoor positioning.

The IMM-UKF algorithm involves three main steps: mode estimation, prediction, and update. In the mode estimation step, the algorithm uses the IMM algorithm to estimate the mode or the system dynamics. In the prediction step, the algorithm uses the system model of the selected Kalman filter to estimate the state of the system at the next time step. In the update step, the algorithm uses the measurements to update the state estimate. The IMM-UKF algorithm has several advantages over other filtering algorithms. First, the algorithm can handle unknown or varying system dynamics by switching between different Kalman filters. Second, the algorithm can estimate the mode or the system dynamics, which can be used for decision-making and control. Third, the algorithm provides a measure of the uncertainty in the state estimate, which can be used for risk assessment and control.

However, the IMM-UKF algorithm has some limitations that should be considered when applying it to real-world problems. First, the algorithm is computationally more expensive than other filtering algorithms due to the multiple Kalman filters and the IMM algorithm. Second, the algorithm may not perform well in situations where the system dynamics are highly nonlinear or non-Gaussian. Third, the algorithm may require tuning of the IMM algorithm parameters, which can be time-consuming. In conclusion, the IMM-UKF filtering algorithm is a powerful technique for state estimation problems where the system dynamics are unknown or vary over time. The algorithm is robust, can handle unknown or varying system dynamics, and provides a measure of the uncertainty in the state estimate. However, the IMM-UKF algorithm has some limitations that should be carefully considered when applying it to real-world problems. Overall, the IMM-UKF algorithm is a valuable tool for state estimation problems in various fields and has many practical applications.

When the tracked target is maneuvering, due to the uncertainty of the maneuvering motion model, it is difficult to describe the actual target motion state with any single target motion model.Interactive multiple model (IMM) realizes the tracking of maneuvering targets by introducing multiple target motion models and weighting the state estimation of each model according to a certain probability.From the perspective of the motion model, a multi-model method is used to improve the positioning accuracy [7]. This can combine the IMM algorithm with the UKF algorithm. This is the multi-model insensitive Kalman filter (IMM-UKF) algorithm.In this way, the advantages of the interactive multi-model algorithm and the UKF filtering algorithm can be combined to obtain a better filtering effect.

3. Multi-target tracking system based on adaptive UFK

3.1. Basic principles of multi-target tracking

The principle of multi-target tracking is shown in Figure 1 below. First, by adopting the cross positioning method, the passive positioning system can obtain multiple cross points at the same time, and output the positioning points after processing the ghost wave points, and then it will delete these positioning points through the tracking gati.Tracking gate is a decision threshold, but it provides a tool. How to use this tool reasonably is the problem to be studied by the data association algorithm.Next, the candidate points in the gate are correctly paired and associated with the corresponding target through data association. Data association is also an important part of multitarget tracking.The quality of the data association algorithm determines whether the positioning point track and the existing target track can be correctly associated and paired, which greatly affects the tracking performance of multiple targets.There is no target track at the beginning, so the first step is to start the target track first. This is the first and most important part of target tracking.Therefore, this link can directly determine the accuracy of the follow-up tracking target. If the initial trajectory is incorrect, the follow-up tracking target must be wrong.When the multi-target trajectory is successfully initiated and confirmed, many stable target trajectories are formed. After that, the number of basic moving targets and basic functional parameters can be determined, and then they can be transmitted to the target tracking filter and the target trajectory can be maintained.When the target loses track due to some reasons, the tracking of the target must be terminated in time according to certain judgment rules, otherwise the correct tracking effect will not be obtained, and the amount of data processing will increase. Finally, the processed track is displayed on the monitor in real time.

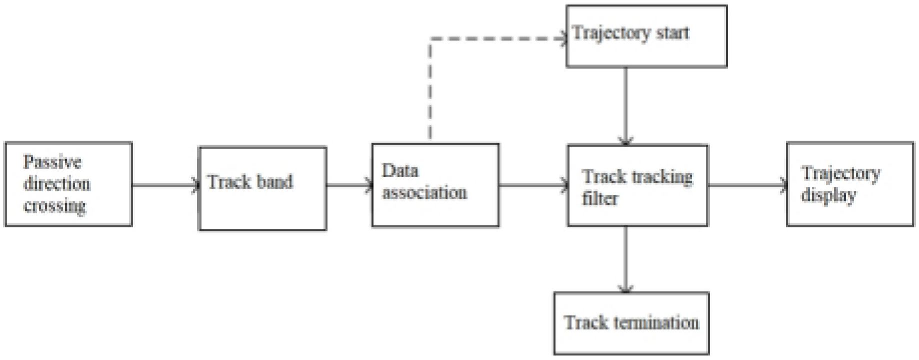

Figure. 1. Schematic diagram of multi-target tracking

3.2. The hardware design of the system

The system structure block diagram is shown as in Figure 2.

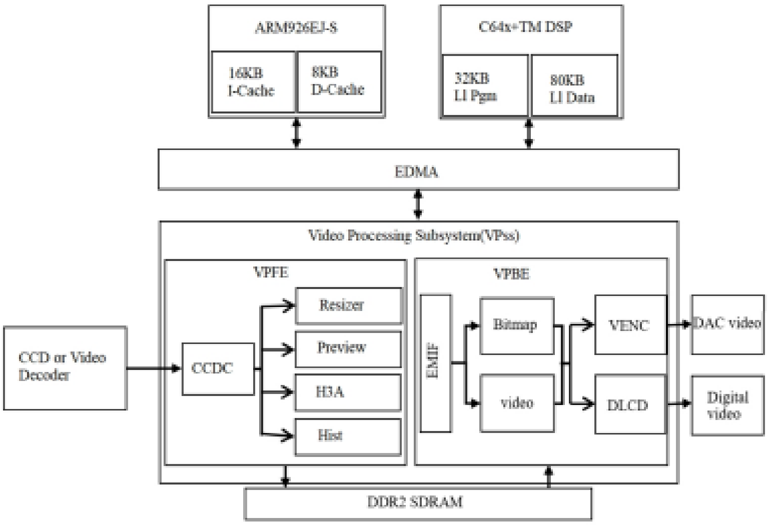

Figure. 2. System structure block diagram

3.3. System software design

System software flow: Based on the unique dual-core architecture of the system hardware, its software development is divided into two parts: ARM and DSP. ARM is responsible for the entire DM6446 system control and data acquisition and storage; DSP is responsible for processing the video data [8].

The essence of target tracking is to extract moving targets from the video sequence, and compare them with similarity, and finally get its moving trajectory. The specific flow chart of this algorithm is shown in Figure 3 [9-10].

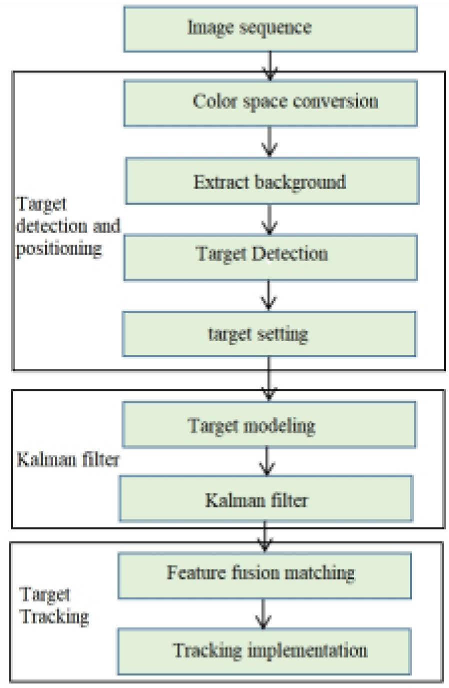

Figure. 3. Algorithm flow chart

4. Conclusion

The rapid development of modern technology has led to the maturity of computer technology and network communication technology. With the development of these technologies, new and highly practical automatic control devices such as the multi-target tracking system have gained attention. Multi-target tracking systems are used in various applications such as video surveillance, radar tracking, and autonomous vehicle navigation. These systems are designed to track multiple targets in real-time and provide accurate information about their location, speed, and direction of movement. This paper proposes a multi-target tracking system based on adaptive filtering algorithms. Adaptive filtering algorithms have been widely used in many fields, including signal processing, control systems, and robotics. The proposed system uses adaptive filtering algorithms to estimate the state of the targets and track them in real-time. The system is designed to adapt to changes in the environment and target behavior, making it suitable for complex tracking scenarios.

The proposed multi-target tracking system has several advantages over existing tracking systems. First, the system can handle multiple targets and track them in real-time, providing accurate and timely information about their location and behavior. Second, the system is adaptive and can adjust to changes in the environment and target behavior, making it suitable for complex tracking scenarios. Third, the system is based on well-established adaptive filtering algorithms, making it reliable and easy to implement. However, the proposed multi-target tracking system also has some limitations that should be considered when applying it to real-world scenarios. First, the system may not perform well in situations where the targets are occluded or closely spaced. Second, the system may require a significant amount of computational resources, which can limit its use in resource-constrained environments. Third, the system may require extensive calibration and tuning, which can be time-consuming.

In conclusion, the proposed multi-target tracking system based on adaptive filtering algorithms is a promising approach for tracking multiple targets in real-time. With the emergence of more algorithms and technologies, there is potential for further progress in the development of multi-target tracking systems. However, the limitations of the proposed system should be carefully considered when applying it to real-world scenarios. Overall, the proposed system is a valuable contribution to the field of multi-target tracking and has many practical applications.

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