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An Adaptive Kalman Filter for Video-Based Tracking with Dynamic Adaptation of Covariance Matrices

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***Abstract*— This paper presents an adaptive Kalman filter for video-based object tracking, in which the process and measurement covariance matrices are updated dynamically in real time. The proposed approach is based on a linear stochastic model without a control input, which is justified by the characteristics of video-based observation. The state vector includes position, velocity, and acceleration components, enabling a more accurate representation of motion dynamics. The main contribution of the study is the development of an adaptive algorithmic structure for estimating the covariance matrices based on innovation statistics. This approach improves consistency between the model and measurements under varying conditions and in the presence of noise. The effectiveness of the proposed method is evaluated through numerical simulation. The results demonstrate a significant reduction in the root mean square error (RMSE) in estimating position and velocity compared to unfiltered measurements and the classical Kalman filter. These results confirm the applicability of the proposed approach to video-based measurement systems.**

Keywords—Adaptive Kalman filter, video-based object tracking, covariance matrix estimation, innovation-based adaptation, state estimation, measurement noise.

I. INTRODUCTION

In recent years, video-based observation has emerged as one of the most promising approaches for real-time measurement and tracking of object motion [1]-[4]. Owing to advances in digital imaging technologies, computer vision, and computational resources, this approach has found wide application in autonomous transportation systems, robotics, industrial automation, security systems, and intelligent transportation systems [5]-[8]. The main advantages include non-contact measurement, the ability to simultaneously observe multiple objects, and the relatively low cost of the measurement infrastructure [9], [10].

Despite these advantages, video-based measurements are associated with a number of limitations that significantly affect the accuracy of the obtained results [11]-[14]. These include image noise, limited spatial and temporal resolution, and inaccuracies in object localization. External factors such as illumination variations, occlusions, and dynamic scene changes also influence the results [15]-[18]. One significant challenge is velocity estimation, which is derived from position and is therefore sensitive to noise and discretization.

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In practice, these limitations are addressed using state estimation algorithms, among which the Kalman filter and its variants are the most widely used [19]. The classical Kalman filter provides optimal recursive estimation when the statistical characteristics of the noise are known; however, its performance strongly depends on the proper selection of the process and measurement covariance matrices [20]-[25]. Under real-world conditions, these parameters are often unknown or time-varying, which leads to degraded accuracy and the presence of systematic deviations in the estimates [19], [23], [26]-[31].

In this regard, adaptive approaches have been developed that update the covariance matrices during filter operation. In this paper, an adaptive Kalman filter for video-based object tracking is proposed, in which the process and measurement covariance matrices are dynamically estimated based on innovation statistics. Unlike classical implementations, the proposed method accounts for changing observation conditions and the dynamics of the tracked object, enabling improved agreement between the model and the measurement information.

The main contribution of this study is the development of an adaptive algorithmic framework that ensures improved accuracy and robustness in estimating the position and velocity of the object. By incorporating an extended state vector and dynamically adapting the covariance matrices, a more accurate representation of the process is achieved, along with improved suppression of noise effects under varying observation conditions.

II. Mathematical Modeling of the Adaptive Kalman Filter

A. Problem Formulation and Model Selection

The mathematical model of the proposed algorithm is formulated as a linear stochastic model, which enables a formalized description of the dynamics of the observed object and the measurement process in the presence of uncertainty.

The choice of this type of model is motivated by the need to ensure:

- optimal recursive state estimation in the sense of minimum mean square error;
- the possibility for explicit representation and adaptive handling of uncertainty sources through the covariance matrices;
- agreement between the dynamic model and the measurement information under varying observation conditions.

In this context, the system dynamics and the measurement process are described by the following standard form:

$$x_k = Ax_{k-1} + w_k, \qquad w_k \sim N(0, Q_k), \tag{1}$$

$$z_k = Hx_k + v_k, \qquad v_k \sim N(0, R_k), \tag{2}$$

where x_k is the state vector; z_k is the measurement vector; w_k and v_k are stochastic variables representing the process uncertainty and measurement noise, respectively, with covariance matrices Q and R; and H is the measurement matrix.

In general, a control input vector is included in the state equation to describe external influences acting on the system. In the considered formulation, however, the objects are observed via a video stream rather than controlled; thus, no physical control signal is available. The inclusion of such an input through numerical differentiation of the measurements (e.g., via acceleration estimation) amplifies noise components and increases uncertainty, since these quantities are not directly measurable and are highly sensitive to discretization errors and image processing inaccuracies.

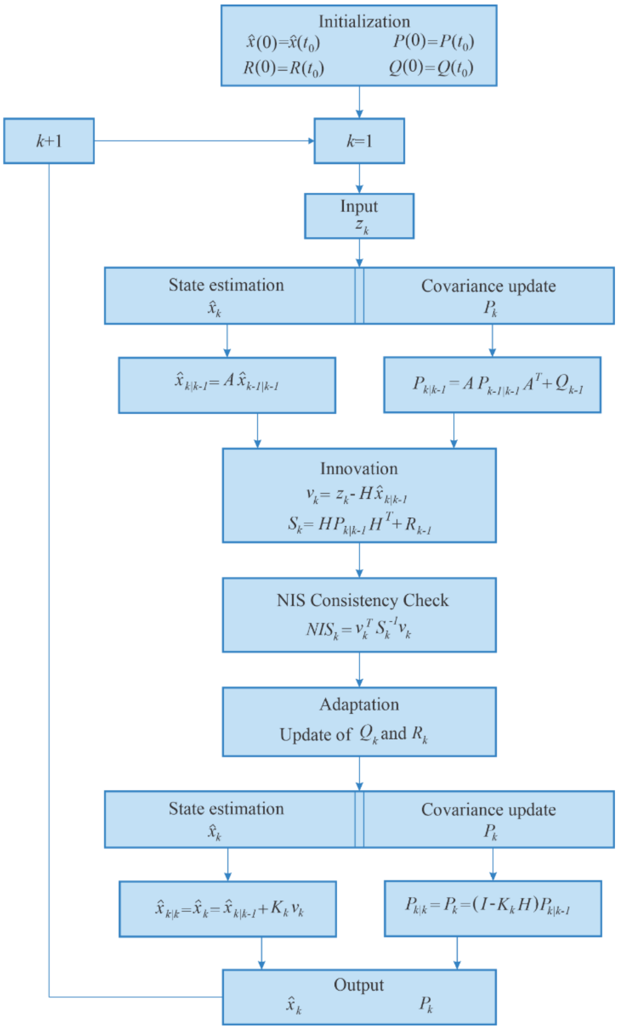


Fig. 1. Block diagram of the adaptive Kalman filter with NIS-based control and dynamic update of the covariance matrices

Therefore, the control input term is omitted from the model, which adopts the reduced form (1). This decision is justified from both physical and metrological perspectives, as it:

- eliminates unobservable quantities;

- reduces model uncertainty;
- enables more accurate estimation of the covariance matrices Q and R;
- improves the robustness of the algorithm under noise, occlusions, and varying frame rates.

As a result, unmodeled variations in the object motion are captured by the stochastic term w_k and its covariance matrix Q, which is dynamically adapted.

The algorithmic structure of the proposed adaptive Kalman filter is presented in Fig. 1. The filtering process is organized into two parallel computational branches, corresponding to the state estimation and the covariance matrix update. These branches operate synchronously and are interconnected through the Kalman gain and the iterative structure of the algorithm.

At each iteration, a prediction of the state and covariance is performed, followed by the computation of the innovation and its covariance. The NIS (Normalized Innovation Squared) criterion is used as a control layer to assess the consistency between the predicted state and the current measurement.

Based on the NIS value, an adaptive update of the covariance matrices Q_k and R_k is carried out, enabling dynamic adjustment of the relative influence of the model and the measurement information at each iteration.

B. Definition of the State Vector

To describe the motion of the object in the image plane, an extended state vector is introduced, which includes the position, velocity, and acceleration components along both axes:

$$x_k = \begin{bmatrix} x_k \\ y_k \\ v_{x,k} \\ v_{y,k} \\ a_{x,k} \\ a_{y,k} \end{bmatrix}, \quad (3)$$

where x_k and y_k denote the current coordinates of the object center in the image plane, $\dot{x}_k$ and $\dot{y}_k$ represent the corresponding velocities, and $a_{x,k}$ and $a_{y,k}$ denote the accelerations along the coordinate axes.

This choice enables a simultaneous description of the current position of the object and its dynamics, accounting not only for the instantaneous velocity but also for its rate of change. The inclusion of acceleration components as states reduces systematic model error under real-world conditions, where motion is rarely characterized by constant velocity. Classical constant-velocity models account for such variations indirectly by increasing the process covariance, which results in increased uncertainty and reduced stability of the estimates. In this approach, acceleration is treated as part of the state, enabling a more physically grounded representation of the process and more accurate prediction of motion, particularly in the presence of abrupt changes or temporary loss of measurements.

From a metrological perspective, this results in a more accurate distribution of uncertainty, as the influence of acceleration is explicitly estimated through the corresponding components of the state covariance matrix rather than being absorbed into the stochastic term.

The selected state vector strikes a balance between model accuracy and computational complexity, while enabling effective adaptation of the process covariance matrix depending on the current dynamic regime.

C. State Transition Model

The state dynamics are described by (1), which defines the evolution of the state in discrete time through the state transition matrix A and the stochastic term w_k, representing the process uncertainty.

Assuming a nearly constant acceleration motion model and discretization with a sampling interval Δt, the state transition matrix A takes the following form:

$$A = \begin{bmatrix} 1 & 0 & \Delta t & 0 & \frac{\Delta t^2}{2} & 0 \\ 0 & 1 & 0 & \Delta t & 0 & \frac{\Delta t^2}{2} \\ 0 & 0 & 1 & 0 & \Delta t & 0 \\ 0 & 0 & 0 & 1 & 0 & \Delta t \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \quad (4)$$

This structure is derived from the kinematic equations of uniformly accelerated motion and provides a physically grounded prediction of the state. Using a model that includes acceleration components reduces systematic error under variable velocity conditions and improves the robustness of the filter in the presence of temporary loss of measurements.

In the considered formulation, deviations from the idealized model are accounted for by the stochastic term w_k, whose intensity is defined by the covariance matrix Q_k, which is adapted in real time.

D. Measurement Model

In the basic formulation of video-based tracking, measurement information is typically limited to the object coordinates in the image plane. In the proposed approach, this model is extended by incorporating velocity components derived from consecutive frames, as they provide additional information about motion dynamics and improve the agreement between the measurement and prediction models.

Therefore, the measurement information is extracted from the video stream in the form of object coordinates and their rates of change [32]. This defines the linear nature of the measurement model described by (2).

In accordance with the defined state vector, the measurement is assumed to include the object coordinates and their velocities; therefore, the measurement matrix takes the following form:

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}, \qquad (5)$$

and the measurement vector is given by:

$$z_k = \begin{bmatrix} x_m(k) \\ y_m(k) \\ \dot{x}_m(k) \\ \dot{y}_m(k) \end{bmatrix}, \qquad (6)$$

where $x_m(k)$ and $y_m(k)$ are the measured coordinates of the object center in the image plane, and $\dot{x}_m(k)$ and $\dot{y}_m(k)$ are the corresponding velocities, obtained from consecutive frames or estimated using a motion estimation algorithm.

In this formulation, accelerations are estimated recursively using the Kalman filter rather than being measured directly. This enables the use of available measurement data while maintaining an extended representation of the object dynamics.

Measurement uncertainty is characterized by the covariance matrix R_k, which accounts for errors in determining the coordinates and velocities. Since the velocities are derived from the measured coordinates, their variances are larger and should be evaluated in accordance with the employed image processing algorithm. The initial values of R_k are determined based on calibration data or a preliminary experimental assessment of the measurement noise. During operation, the matrix is adapted online through analysis of the filter innovations, while the agreement between prediction and measurement is monitored using the Normalized Innovation Squared (NIS) criterion.

This enables dynamic adjustment of the confidence in the measurement data depending on its current quality, ensuring a metrologically sound and data-consistent state estimation in video-based tracking.

E. Process Noise Covariance Matrix

The process noise covariance matrix Q_k characterizes the uncertainty associated with inaccuracies in the dynamic model and unmeasured influences acting on the motion of the object.

In the considered case, these influences are modeled as stochastic variations in acceleration, assuming that its derivative (jerk) is a white noise process. Under this assumption, the process covariance matrix is defined as follows:

$$Q_k = \sigma_j^2 \begin{bmatrix} \frac{\Delta t^5}{20} & 0 & \frac{\Delta t^4}{8} & 0 & \frac{\Delta t^3}{6} & 0 \\ 0 & \frac{\Delta t^5}{20} & 0 & \frac{\Delta t^4}{8} & 0 & \frac{\Delta t^3}{6} \\ \frac{\Delta t^4}{8} & 0 & \frac{\Delta t^3}{3} & 0 & \frac{\Delta t^2}{2} & 0 \\ 0 & \frac{\Delta t^4}{8} & 0 & \frac{\Delta t^3}{3} & 0 & \frac{\Delta t^2}{2} \\ \frac{\Delta t^3}{6} & 0 & \frac{\Delta t^2}{2} & 0 & \Delta t & 0 \\ 0 & \frac{\Delta t^3}{6} & 0 & \frac{\Delta t^2}{2} & 0 & \Delta t \end{bmatrix}, \qquad (7)$$

where σ_j^2 is a parameter defining the intensity of the stochastic variations in acceleration.

This structure ensures agreement between the kinematic model and the stochastic description of the dynamics, accounting for the interdependence between position, velocity, and acceleration.

In the proposed approach, the parameter σ_j^2 is treated as an adaptive quantity, updated in real time based on the innovation statistics. In this way, the matrix Q_k dynamically reflects the current motion regime of the object:

- under smooth motion, its values decrease, increasing the confidence in the model;
- under abrupt changes, they increase, allowing for a more flexible response of the filter.

From a metrological perspective, Q_k determines the contribution of model uncertainty to the overall uncertainty of the estimate. Its adaptive determination ensures agreement between the mathematical model and the real process and is a prerequisite for reliable state estimation under varying dynamic conditions.

F. Measurement Noise Covariance Matrix

The measurement noise covariance matrix R_k characterizes the statistical properties of the errors arising in the observation of the quantities in the vector z_k and reflects the uncertainty associated with extracting coordinates and velocities from the video data.

In the general case of two-dimensional coordinate measurements, the matrix takes the following form:

$$R_k = \begin{bmatrix} \sigma_{x,q}^2 & \rho_{xy}\sigma_{x,q}\sigma_{y,q} \\ \rho_{xy}\sigma_{x,q}\sigma_{y,q} & \sigma_{y,q}^2 \end{bmatrix}, \qquad (8)$$

where $\sigma_{x,q}^2$ and $\sigma_{y,q}^2$ are the variances of the measurements, and ρ_{xy} is the correlation coefficient.

In the practical formulation, the measurements along the two axes are assumed to be independent, i.e., $\rho_{xy} = 0$, and the matrix reduces to a diagonal form. For the considered extended measurement vector, the matrix R_k is specified as:

$$R_k = \begin{bmatrix} \sigma_x^2 & 0 & 0 & 0 \\ 0 & \sigma_y^2 & 0 & 0 \\ 0 & 0 & \sigma_{\dot{x}}^2 & 0 \\ 0 & 0 & 0 & \sigma_{\dot{y}}^2 \end{bmatrix}. \quad (9)$$

In (9), the variances of the velocity components are higher, as they are not measured directly but are obtained through numerical differentiation of the coordinates, which leads to amplification of measurement noise.

The matrix R_k summarizes the influence of the main sources of error, including image discretization, sensor noise, inaccuracies in object localization, illumination variations, and calibration errors.

The initial values of the elements of R_k are determined experimentally through analysis of the variations of the measured coordinates for a static object.

In real time, the matrix R_k is adapted based on the innovation:

$$\nu_k = z_k - H_k \hat{x}_{k|k-1}, \quad (10)$$

using exponential weighting

$$R_k = (1 - \lambda_R) R_{k-1} + \lambda_R (\nu_k \nu_k^T - H_k P_{k|k-1} H_k^T), \quad (11)$$

where $\lambda_R \in (0,1)$ is the adaptation coefficient; $\hat{x}_{k|k-1}$ is the a priori (predicted) estimate of the state vector at time k, computed based on the information available up to time $k-1$; and $P_{k|k-1}$ is the corresponding covariance matrix of the prediction error [33].

where the value of NIS_k is compared with the confidence bounds of the χ^2 distribution with degrees of freedom equal to the dimension of the measurement.

The NIS criterion is used to monitor the agreement between the model and the measurements, serving as the basis for adaptive updating of the covariance matrices at each iteration of the algorithm.

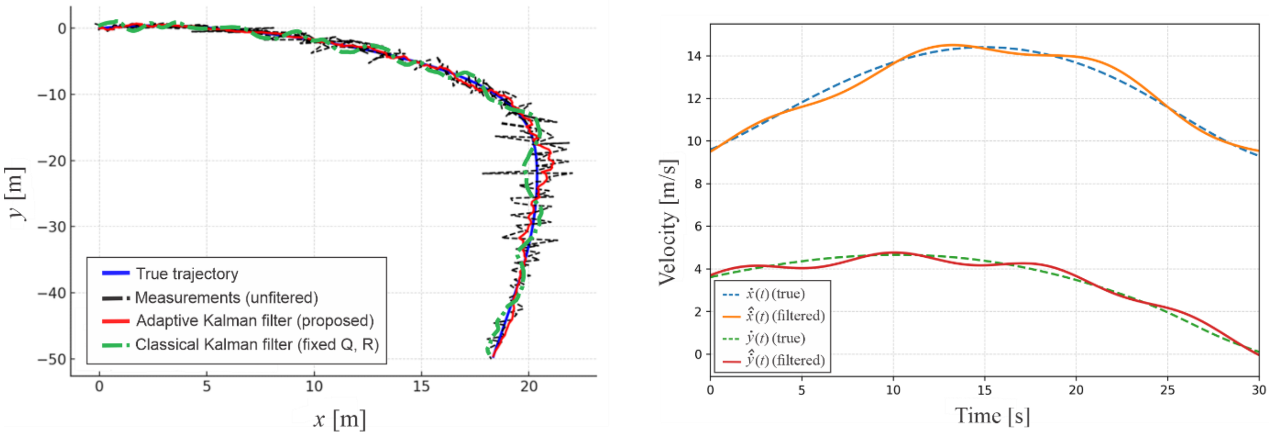
If a deviation occurs outside the permissible interval, the matrix R_k is adjusted, which reduces the influence of inconsistent measurements and ensures robust filter performance under noisy or atypical conditions.

From a metrological perspective, R_k defines the confidence bounds of the measurements and, together with Q_k, determines the overall uncertainty of the estimate. Its adaptive determination ensures statistical agreement and metrological traceability under varying observation conditions.

III. Modeling and Simulation Analysis

Numerical simulations of the motion of the object's projection in the image plane, described by a discrete stochastic model, were performed to evaluate the effectiveness of the proposed adaptive Kalman filter. The state dynamics and the measurement process are represented by the equations defined in Section 2, while uncertainties are modeled through the covariance matrices Q_k and R_k, which are dynamically adapted over time.

The simulation was implemented in the MATLAB environment using a constant sampling interval $\Delta t = 0.1$ s. The motion included smooth variations in velocity and random variations in acceleration. The coordinate



a) *b)*

Fig. 2. Simulation results of the proposed adaptive Kalman filter: (a) object trajectory in the image plane - comparison between true, measured, and estimated trajectories; (b) velocity components - comparison between true velocities $\dot{x}(t), \dot{y}(t)$ and estimated velocities $\hat{\dot{x}}(t), \hat{\dot{y}}(t)$.

The agreement between the model and the measurements is evaluated using the Normalized Innovation Squared (NIS) criterion:

$$\mathrm{NIS}_k = \nu_k^T S_k^{-1} \nu_k, \qquad S_k = H_k P_{k|k-1} H_k^T + R_k, \quad (12)$$

measurements were modeled by adding Gaussian noise with different variances along the coordinate axes to mimic real-world observation conditions in video-based measurement systems.

The simulation results are presented in Fig. 2. Fig. 2a shows the trajectory of the object in the image plane, where a good agreement between the true and estimated trajectories is observed, along with a significant reduction of noise-induced deviations in the measurements. The filtered trajectory smoothly follows the true motion, effectively attenuating the high-frequency components caused by measurement noise.

The quantitative evaluation of accuracy is performed using the root mean square error (RMSE), defined as:

$$RMSE = \sqrt{\frac{1}{N}(x_k - \hat{x}_k)^2}, \quad (13)$$

where x_k and $\hat{x}_k$ denote the true and estimated coordinates of the object, respectively.

From the graphical representation, it can be observed that the unfiltered measurements are strongly affected by noise, resulting in significant deviations from the true trajectory. When a classical Kalman filter is applied, effective attenuation of high-frequency noise is achieved; however, due to the use of fixed covariance matrices, inertia in the estimate is observed, manifested as lag and local systematic deviations in regions with faster variations in motion.

The proposed adaptive filter reduces this effect through dynamic adaptation of the covariance matrices, enabling faster response to changes in the signal and providing improved estimation accuracy over the entire motion range.

The quantitative results presented in Table 1 confirm the above analysis.

TABLE 1 ROOT MEAN SQUARE ERROR (RMSE) FOR POSITION AND VELOCITY ESTIMATION USING DIFFERENT METHODS

Estimated quantity	Method	RMSE
Position (coordinates)	Unfiltered measurements	1.2944 m
Position (coordinates)	Classical Kalman filter	0.5173 m
Position (coordinates)	Adaptive Kalman filter	0.2140 m
Velocity ($\dot{x}(t)$)	Adaptive Kalman filter	0.238 m/s
Velocity ($\dot{y}(t)$)	Adaptive Kalman filter	0.203 m/s

Fig. 2b presents a comparison between the true velocities $\dot{x}(t)$ and $\dot{y}(t)$ and the estimated velocities $\hat{\dot{x}}(t)$ and $\hat{\dot{y}}(t)$ obtained using the proposed adaptive filter. From the graphical representation, it can be observed that the estimated velocities closely follow the overall trend of the true velocities under smoothly varying motion conditions.

The small deviations observed between the true and estimated values are attributed to the influence of measurement noise and the recursive nature of the estimation process. The obtained results indicate that the proposed filter provides stable estimation of the velocity components $\dot{x}(t)$ and $\dot{y}(t)$, without introducing significant high-frequency oscillations in the estimates.

The quantitative evaluation of accuracy is performed using the root mean square error (RMSE), with (13) applied analogously to the velocity components. The corresponding quantitative results for the velocity estimation error are summarized in Table 1.

IV. CONCLUSION

In this work, an adaptive Kalman filter for video-based object tracking is developed, in which the process and measurement covariance matrices are dynamically updated in real time. The proposed approach is based on a linear stochastic model without the inclusion of a control input, which is justified by the characteristics of video-based observation.

By incorporating position, velocity, and acceleration components into the state vector, a more accurate representation of motion dynamics is achieved, providing improved agreement between the model and the measurements. The adaptive estimation of the covariance matrices enables the filter to adjust to changing noise characteristics and dynamic regimes, resulting in enhanced robustness and estimation accuracy.

From a scientific perspective, the main contribution of this study lies in the development of an adaptive algorithmic structure in which the filter parameters are updated based on the statistical characteristics of the innovation. The use of the Normalized Innovation Squared (NIS) criterion as a control mechanism enables a formalized assessment of the filter behavior and provides the basis for targeted adjustment of its parameters according to the current observation conditions. In this way, a mechanism for dynamic balancing between the model and the measurement information is achieved, extending classical approaches based on fixed parameters.

From a metrological perspective, the proposed approach can be interpreted as a mechanism for dynamic management of uncertainty in the estimation process. In this context, the covariance matrices acquire the role of carriers of confidence-related information, which is updated in real time depending on the quality of the measurements and the nature of the motion. This enables the integration and weighting of information with different levels of reliability, ensuring more robust algorithm performance in the presence of noise and varying observation conditions.

The simulation results demonstrate a significant reduction in root mean square error compared to unfiltered measurements, as well as additional improvement when applying the proposed adaptive approach. The obtained results confirm the effectiveness of the method for both position estimation and velocity determination.

The results indicate that the proposed approach is suitable for application in video-based tracking systems operating under noisy and time-varying observation conditions.

Despite the achieved results, the proposed approach offers opportunities for further development. Future research may focus on experimental validation under real-world conditions, as well as on extending the model to nonlinear dynamic systems. In addition, the integration with advanced image processing algorithms and adaptive parameter estimation methods could lead to enhanced robustness in the presence of complex scenes, occlusions, and varying observation conditions. Furthermore, the influence of the selection of adaptive parameters and the characteristics of the measurement noise on the stability of the algorithm represents an important direction for more in-depth investigation.

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