Frontiers in Engineering
ISSN Print: 3104-4298
ISSN Online: 3104-4301
CD ISSN: 3104-431X
https://doi.org/10.63313/FE.9004

A Real-Time Trajectory Estimation Algorithm for the Virtual Side of an AGV Digital Twin Based on UKF

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How to cite this paper: Zhang, X. Y., & Liang, X. Y. (2026). A Real-Time Trajectory Estimation Algorithm for the Virtual Side of an AGV Digital Twin Based on UKF. *Frontiers in Engineering*, 1(2), 1-9. ISSN Print: 3104-4298; ISSN Online: 3104-4301.
https://doi.org/10.63313/FE.9004
Published: 2026-03-16

Abstract

To address the insufficient trajectory estimation accuracy of the virtual side in AGV digital twins under intermittent measurements, a real-time trajectory estimation algorithm that integrates the Unscented Kalman Filter (UKF) with periodic station-based correction is proposed. Nonlinear state and measurement equations adapted to AGV motion characteristics are constructed. The UKF is employed to realize real-time position recursion based on intermittent velocity and heading information, while high-precision position information from fixed stations is used to correct accumulated errors. Simulation results demonstrate that the proposed algorithm can effectively suppress error accumulation and achieve accurate tracking of the physical trajectory by the virtual side, providing technical support for precise trajectory replication in AGV digital twin systems.

Keywords

AGV digital twin; trajectory estimation; unscented Kalman filter (UKF); intermittent measurements; station-based correction

1. Introduction

With the deep integration of intelligent manufacturing and the Industry 4.0 concept [1][2], digital twin technology—characterized by virtual–physical mapping, real-time interaction, and dynamic evolution—has become a key enabling technology for improving the operational efficiency and task accuracy of Automated Guided Vehicles (AGVs) [3]. In AGV digital twin systems, the virtual side must accurately replicate the motion trajectory of the physical AGV to provide reliable data support for path planning optimization, fault early warning and diagnosis, and operation process management. Therefore, the real-time performance and accuracy of trajectory estimation directly determine the application value of the digital twin system.

Parrott et al. were among the first to define the concept of the digital twin in the academic field [4]. Digital twin technology constructs a virtual representation of a physical entity through digital means and integrates historical data, real-time sensor data, and algorithmic models to enable simulation, validation, prediction, and control throughout the entire lifecycle of the physical entity. In studies related to AGV digital twins in logistics scenarios, current research mainly focuses on two directions. The first is the digital twin of the AGV itself, which builds a virtual simulation model of a single AGV to represent its physical characteristics and operating conditions in real time. The second is the digital twin of workshop logistics systems, which establishes virtual models covering workshop layouts, logistics routes, and AGV operating states to support logistics management and production scheduling decisions.

At present, trajectory estimation on the virtual side of AGV digital twin systems mostly relies on position, velocity, and other sensor data transmitted from the physical side. However, in real industrial environments, due to objective constraints such as communication bandwidth limitations and complex environmental interference, the virtual side cannot continuously receive real-time data from the physical AGV and can only intermittently obtain non-position measurements such as velocity and heading angle. If trajectory estimation relies solely on such intermittent measurements, accumulated errors are likely to cause deviation between the virtual trajectory and the actual physical motion, preventing accurate virtual–physical synchronization and ultimately limiting the core effectiveness of AGV digital twin systems.

To address trajectory estimation accuracy under intermittent measurements, various filtering and estimation algorithms have been proposed. Among them, Kalman filtering and its variants have been widely applied in motion target localization due to their favorable state estimation performance [5]. Compared with the Extended Kalman Filter (EKF), which requires linearization of nonlinear systems and is prone to linearization errors, the Unscented Kalman Filter (UKF) employs the unscented transformation to approximate the probability distribution of states through sigma points. This allows UKF to more accurately handle the nonlinear characteristics of AGV motion and achieve higher accuracy and stability in state estimation for nonholonomic systems [6][7].

It is worth noting that although filtering algorithms can suppress error accumulation to some extent, long-term estimation bias under intermittent measurements is still difficult to eliminate completely. Fixed stations commonly deployed in AGV operating environments—such as charging points and docking stations—provide high-precision positioning capabilities. By incorporating station position information as correction constraints into the filtering process, accumulated errors can be effectively corrected, thereby improving long-term trajectory estimation reliability. Based on this insight, this paper proposes a real-time trajectory estimation algorithm that integrates UKF with periodic station-based correction for the intermittent measurement scenario of AGV digital twin virtual sides.

The main contributions of this paper include: constructing nonlinear state and measurement equations adapted to AGV motion characteristics; designing a UKF-based trajectory prediction mechanism that achieves real-time position recursion using intermittent velocity and heading information; and introducing a station correction mechanism to correct estimation errors when the AGV passes fixed stations.

The research results provide technical reference for precise trajectory replication in AGV digital twin systems and promote the deep application of digital twin technology in intelligent manufacturing.

2. Problem Formulation

This paper focuses on the real-time trajectory estimation problem of the virtual side in AGV digital twin systems under intermittent measurements. The core requirement is to utilize intermittently transmitted velocity and heading information from the physical AGV to accurately estimate its real-time position on the virtual side, while correcting accumulated estimation errors using high-precision position information obtained when the AGV passes fixed stations, thus ensuring virtual–physical synchronization.

In AGV digital twin systems, information transmission between the physical side and the virtual side is asynchronous. Due to communication bandwidth limitations and interference in complex industrial environments, the virtual side cannot continuously receive real-time position data from the physical AGV and can only receive discrete velocity and heading angle data at fixed intervals. The virtual side must therefore rely on these intermittent measurements to recursively estimate the AGV position in real time. Meanwhile, fixed stations (e.g., charging points and docking points) are deployed in AGV operating environments. When the AGV passes these stations, the virtual side can obtain high-precision actual position information through station positioning devices.

The core objective of this problem is to design a trajectory estimation algorithm suitable for intermittent measurement scenarios. On one hand, the algorithm must accurately predict AGV positions at each time step based on intermittently received velocity and heading information. On the other hand, it must effectively correct accumulated estimation errors using high-precision station position information when the AGV passes fixed stations, ensuring that the virtual trajectory accurately tracks the physical AGV trajectory.

When solving this trajectory estimation problem, system modeling and algorithm design must consider the following constraints:

- Nonlinearity constraint: AGV motion, especially during steering, exhibits significant nonlinear characteristics. The trajectory estimation algorithm must accommodate nonlinear motion models and avoid errors introduced by linear approximations.

- Intermittent measurement constraint: The virtual side can only intermittently obtain velocity and heading measurements without continuous position input. The algorithm must support state recursion based on historical measurements while suppressing error accumulation.
- Station correction constraint: High-precision position data are available only when the AGV passes fixed stations. The correction process must balance estimation smoothness and correction accuracy to avoid trajectory discontinuities caused by single corrections.

The block diagram of the proposed UKF-based real-time trajectory estimation algorithm for the virtual side of an AGV digital twin is shown in Figure 1.

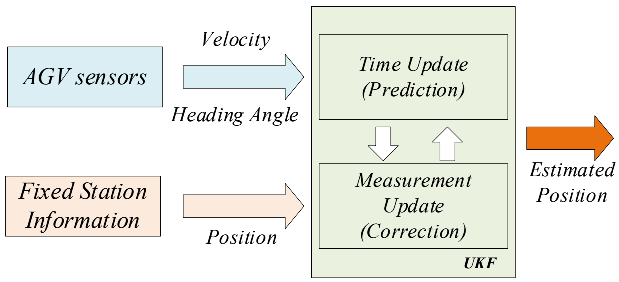

Figure 1. Block diagram of the UKF-based real-time trajectory estimation algorithm for the virtual side of an AGV digital twin

3.Real-Time Trajectory Estimation Algorithm

3.1. Unscented Transformation

The core of the UKF is the Unscented Transformation (UT) [8][9]. Consider a nonlinear function and a random variable following a Gaussian distribution with mean and covariance. The UT first selects a set of discrete points, known as sigma points, from the distribution according to specific rules. The sampling process ensures that the mean and covariance of the sigma point set match those of the original random variable. The nonlinear function is then applied to each sigma point to obtain a transformed sigma point set. The weighted mean and covariance of the transformed points approximate the mean and covariance after nonlinear transformation.

Given the mean and covariance of a random variable, the symmetric sampling method yields the sigma point set and corresponding weights as follows [10]:

$$[\chi_1 \quad \chi_2 \quad \cdots \quad \chi_{2n+1}] = [\bar{\mathbf{x}} \quad \bar{\mathbf{x}}\mathbf{I}_{1\times n} - \gamma_\chi\sqrt{\boldsymbol{P}} \quad \bar{\mathbf{x}}\mathbf{I}_{1\times n} + \gamma_\chi\sqrt{\boldsymbol{P}}] \tag{1}$$

$$W_i^{(m)} = \begin{cases} \dfrac{\lambda}{n+\lambda} & ,i=1 \\ \dfrac{1}{2(n+\lambda)} & ,i=2,3,\cdots,2n+1 \end{cases} \tag{2}$$

$$W_i^{(c)} = \begin{cases} \dfrac{\lambda}{n+\lambda} + (1-\alpha_0{}^2+\beta) & ,i=1 \\ \dfrac{1}{2(n+\lambda)} & ,i=2,3,\cdots,2n+1 \end{cases} \tag{3}$$

where is a vector of ones; and are the mean and covariance weights of the i-th sigma point; is the dimension of the random variable; is a positive scaling parameter determining the distance between sigma points and the mean (set to in this paper); and are parameters ensuring the semi-positive definiteness of the covariance matrix (set to); assumes a Gaussian distribution.

3.2. Unscented Kalman Filter

Consider the following nonlinear continuous system, i.e., the UKF model:

$$\begin{cases} \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x},\mathbf{u}) + \mathbf{G}(\mathbf{x})\mathbf{w} \\ \mathbf{y}_{\mathrm{m}} = \mathbf{h}(\mathbf{x}) + \mathbf{v} \end{cases}$$

where the first equation is the state equation and the second is the measurement equation; denotes the system state; denotes the measurement; and represent process noise and measurement noise, respectively. Both are zero-mean Gaussian white noises and are uncorrelated:

$$E[\mathbf{w}\mathbf{w}^T] = \mathbf{Q}, E[\mathbf{v}\mathbf{v}^T] = \mathbf{R}, E[\mathbf{w}\mathbf{v}^T] = \mathbf{0}$$

The UKF algorithm corresponding to this model is shown in Table 1.

Table 1. Unscented Kalman Filter Algorithm

Unscented Kalman Filtering Algorithm for Nonlinear Continuous Systems
Step 1 Initialization： $\hat{\boldsymbol{x}}_0 = E[\mathbf{x}_0], \boldsymbol{P}_0 = E[(\mathbf{x}_0 - \hat{\mathbf{x}}_0)\cdot(\mathbf{x}_0 - \hat{\mathbf{x}}_0)^T]$ Step 2 Determine the weights of sigma points： $W_i^{(m)} = \begin{cases} \dfrac{\lambda}{n+\lambda} & ,i=1 \\ \dfrac{1}{2(n+\lambda)} & ,i=2,3,\cdots,2n+1 \end{cases}$ $W_i^{(c)} = \begin{cases} \dfrac{\lambda}{n+\lambda} + (1-\alpha_0{}^2+\beta) & ,i=1 \\ \dfrac{1}{2(n+\lambda)} & ,i=2,3,\cdots,2n+1 \end{cases}$ Step 3 Determine the sampling time Δt Step 4 State prediction at time k(time update)： $\chi_{k-1} = [\hat{\boldsymbol{x}}_{k-1} \quad \hat{\boldsymbol{x}}_{k-1}\mathbf{I}_{1\times n} - \gamma_\chi\sqrt{\boldsymbol{P}_{k-1}} \quad \hat{\boldsymbol{x}}_{k-1}\mathbf{I}_{1\times n} + \gamma_\chi\sqrt{\boldsymbol{P}_{k-1}}]$ $\boldsymbol{\chi}^*_{i,k/k-1} = \boldsymbol{\chi}_{i,k-1} + f(\boldsymbol{\chi}_{i,k-1}, \mathbf{u}_{k-1})\Delta t$ $\hat{\mathbf{x}}_{k/k-1} = \sum_{i=1}^{2n+1} W_i^{(\mathrm{m})}\boldsymbol{\chi}^*_{i,k/k-1}$ $\boldsymbol{P}_{k/k-1} = \sum_{i=1}^{2n+1} W_i^{(\mathrm{c})}(\boldsymbol{\chi}^*_{i,k/k-1} - \hat{\mathbf{x}}_{k/k-1})(\boldsymbol{\chi}^*_{i,k/k-1} - \hat{\mathbf{x}}_{k/k-1})^T + \boldsymbol{G}(\hat{\mathbf{x}}_{k-1})\boldsymbol{Q}_{k-1}\boldsymbol{G}^T(\hat{\mathbf{x}}_{k-1})\Delta t$ Step 5 Measurement correction at time k(measurement update)： $\chi_{k/k-1} = [\hat{\mathbf{x}}_{k/k-1} \quad \hat{\mathbf{x}}_{k/k-1} - \gamma_\chi\sqrt{\boldsymbol{P}_{k/k-1}} \quad \hat{\mathbf{x}}_{k/k-1} + \gamma_\chi\sqrt{\boldsymbol{P}_{k/k-1}}]$

$$\boldsymbol{y}_{i,k/k-1} = \mathbf{h}(\boldsymbol{\chi}_{i,k/k-1})$$
$$\hat{\mathbf{y}}_k = \sum_{i=1}^{2n+1} W_i^{(\mathrm{m})} \boldsymbol{y}_{i,k/k-1}$$
$$\mathbf{P}_{xy,k} = \sum_{i=1}^{2n+1} W_i^{(\mathrm{c})} (\boldsymbol{\chi}_{i,k/k-1} - \hat{\mathbf{x}}_{k/k-1})(\boldsymbol{y}_{i,k/k-1} - \hat{\mathbf{y}}_k)^T$$
$$\mathbf{P}_{yy,k} = \sum_{i=1}^{2n+1} W_i^{(\mathrm{c})} (\boldsymbol{y}_{i,k/k-1} - \hat{\mathbf{y}}_k)(\boldsymbol{y}_{i,k/k-1} - \hat{\mathbf{y}}_k)^T + \mathbf{R}$$
$$\mathbf{K}_k = \mathbf{P}_{xy,k}\mathbf{P}_{yy,k}^{-1}$$
$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_{k/k-1} + \mathbf{K}_k(\mathbf{y}_{\mathrm{m}} - \hat{\mathbf{y}}_k)$$
$$\mathbf{P}_k = \mathbf{P}_{k/k-1} - \mathbf{K}_k\mathbf{P}_{yy,k}\mathbf{K}_k^T$$

Step 6 Output the state estimate $\hat{\mathbf{x}}_k$, $k = k+1$ return Step4

UKF initializes the state estimate and covariance, determines the sigma point sampling strategy and corresponding weights, and sets the sampling interval. During the time update, sigma points are propagated through the nonlinear state equation to obtain predicted state mean and covariance. During the measurement update, predicted measurements are obtained using UT, and the actual measurements are fused with predicted measurements to update the state estimate and covariance.

3.3. UKF Model for Trajectory Estimation

In the trajectory estimation algorithm based on the Unscented Kalman Filter (UKF), system modeling is the core component [11]. The AGV regulates the speeds of its left and right wheels to control its linear velocity and heading angle, while its lateral displacement is determined jointly by the heading angle and linear velocity. The system state vector is defined as:

$$\mathbf{x} = [p_x \quad p_y \quad \psi \quad V]^T \tag{6}$$

(p_x, p_y) denotes the position information of the AGV, ψ is the heading angle, and V is the linear velocity.

The state equation of the trajectory estimation system is designed as follows:

$$\begin{bmatrix} \dot{p}_x \\ \dot{p}_y \\ \dot{\psi} \\ \dot{V} \end{bmatrix} = \begin{bmatrix} V\cos\psi + w_x \\ V\sin\psi + w_y \\ w_\psi \\ w_V \end{bmatrix}, \quad \mathbf{f}(\mathbf{x}) = \begin{bmatrix} V\cos\psi \\ V\sin\psi \\ 0 \\ 0 \end{bmatrix} \tag{7}$$

$\mathbf{w} = [w_x \quad w_y \quad w_\psi \quad w_V]^T$ where represents the system noise that excites the state variation.

$$\mathrm{w} \sim N(\mathbf{0}, \mathbf{Q}), \mathbf{Q} = diag(\sigma_x^2, \sigma_y^2, \sigma_\psi^2, \sigma_V^2) \tag{8}$$

During each cycle, the digital-twin virtual side receives sensor information consisting of the AGV's heading angle and linear velocity. Therefore, the measurement equation is defined as:

$$\begin{bmatrix}\psi_m\\V_m\end{bmatrix}=\begin{bmatrix}\psi\\V\end{bmatrix}+\begin{bmatrix}v_\psi\\v_V\end{bmatrix},\quad \mathbf{h}(\mathbf{x})=\begin{bmatrix}\psi\\V\end{bmatrix} \tag{9}$$

The trajectory estimation system composed of Eqs. (7) (9) can be used to estimate the trajectory. Although it can suppress error accumulation to a certain extent, the estimation bias under long-term intermittent measurements is still difficult to eliminate completely due to the lack of position correction. Therefore, this paper introduces high-precision position information from fixed stations to correct the accumulated estimation error. The newly designed measurement equation is:

$$\begin{bmatrix}p_{xm}\\p_{ym}\\\psi_m\\V_m\end{bmatrix}=\begin{bmatrix}p_x\\p_y\\\psi\\V\end{bmatrix}+\begin{bmatrix}v_x\\v_y\\v_\psi\\v_V\end{bmatrix},\quad \mathbf{h}(\mathbf{x})=\begin{bmatrix}p_x\\p_y\\\psi\\V\end{bmatrix} \tag{10}$$

$\mathbf{y}_m=[p_{xm}\quad p_{ym}\quad \psi_m\quad V_m]^T$ is the measurement vector and $\mathbf{v}=[v_x\quad v_y\quad v_\psi\quad v_V]^T$ is the measurement noise.

$$\mathrm{v}\sim N(\mathbf{0},\mathbf{R}),\mathbf{R}=diag(\sigma_{xm}^2,\sigma_{ym}^2,\sigma_{\psi m}^2,\sigma_{Vm}^2) \tag{11}$$

When the AGV is outside a fixed station, $\sigma_{xm}^2,\sigma_{ym}^2$ is set to infinity, which means that the position measurement update is performed only when the AGV passes through a fixed station.

At this point, the UKF model for trajectory estimation has been fully established, as shown in Eq. (12).

$$\begin{bmatrix}\dot{p}_x\\\dot{p}_y\\\dot{\psi}\\\dot{V}\end{bmatrix}=\begin{bmatrix}V\cos\psi+w_x\\V\sin\psi+w_y\\w_\psi\\w_V\end{bmatrix},\begin{bmatrix}p_{xm}\\p_{ym}\\\psi_m\\V_m\end{bmatrix}=\begin{bmatrix}p_x\\p_y\\\psi\\V\end{bmatrix}+\begin{bmatrix}v_x\\v_y\\v_\psi\\v_V\end{bmatrix} \tag{12}$$

Combined with the UKF algorithm shown in Table 1, the UKF model in Eq. (12) constitutes the real-time trajectory estimation algorithm for the AGV digital-twin virtual side proposed in this paper.

3.4. Simulation Verification and Result Analysis

The AGV is placed at the initial coordinate (0 m, 0 m). A rectangular reference trajectory with a length of 10 m and a width of 10 m is set. The AGV reference trajectory in the Unity-based virtual factory is shown in Figure 2.

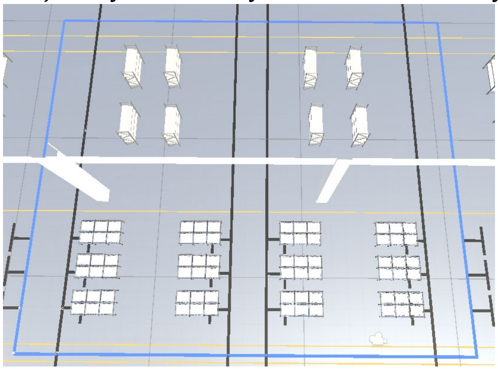

Figure 2. AGV reference trajectory in the virtual factory

The AGV is controlled to start from the initial point, traverse four edges, and return to the starting point. The reference trajectory and actual motion trajectory are shown in Figure 3.

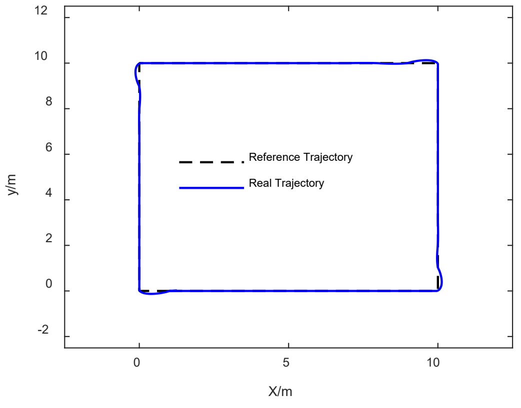

Figure 3. AGV motion trajectory

The sampling interval is set, and AGV velocity and heading information are fed back at each sampling instant. Fixed stations are placed at 1 m intervals. When the AGV reaches a station, position information is fed back for correction. The estimated trajectories obtained using the proposed algorithm are shown in Figure 4.

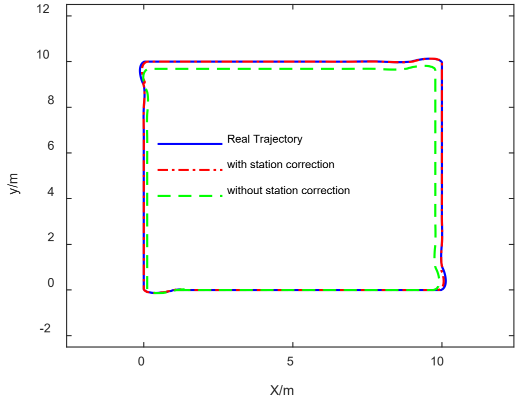

Figure 4. Comparison of trajectory estimation with and without station correction

As shown in Figure 4, the trajectory estimated without station correction deviates from the true AGV trajectory. In contrast, the proposed UKF-based real-time trajectory estimation algorithm with station correction effectively resolves trajectory deviation. The estimated trajectory closely matches the true trajectory and remains smooth without abrupt changes.

4. Conclusion

To address insufficient trajectory estimation accuracy of AGV digital twin virtual sides under intermittent measurements, this paper investigates a real-time trajectory estimation algorithm based on the Unscented Kalman Filter. The main conclusions are as follows:

1. A technical solution integrating UKF with station correction is proposed to address error accumulation caused by intermittent acquisition of velocity and heading information in industrial scenarios, effectively meeting the requirements of precise trajectory replication.
2. A UKF-based trajectory estimation model adapted to AGV motion characteristics is constructed, including position, heading angle, and linear velocity in the state vector. High-precision station position information is used for error correction, enabling accurate real-time trajectory output.
3. Simulation results demonstrate that the proposed UKF-based real-time trajectory estimation algorithm effectively suppresses error accumulation and achieves accurate tracking of the physical AGV trajectory by the virtual side.

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