UDC 621.313 https://doi.org/10.20998/2074-272X.2026.3.08

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Hybrid extended Kalman filter long short-term memory framework for robust state and fault estimation in mobile robots under unknown disturbances

Introduction. *Reliable and accurate state estimation plays a central role in mobile robotics, ensuring effective localization, navigation, and control in uncertain and dynamic environments. Traditional estimation methods such as the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) are widely used for nonlinear systems; however, their performance degrades when facing unknown disturbances or modeling inaccuracies.* ***Problem.*** *In real-world mobile robots, unexpected motor faults and unmeasured disturbances significantly reduce the estimation accuracy and may lead to mission failure. Classical EKF and UKF approaches rely on static models and Gaussian noise assumptions, which make them unsuitable for systems affected by unknown or time-varying uncertainties. The* ***goal*** *of this work is to design and validate a hybrid extended Kalman filter long short-term memory (EKF–LSTM) framework capable of achieving joint state and fault estimation for mobile robots operating under unknown disturbances.* ***Methodology.*** *The proposed approach combines a model-based EKF with an offline-trained LSTM neural network. The EKF performs nonlinear state estimation using physical robot dynamics and noisy Global Positioning System (GPS) measurements, while the LSTM predicts additive motor faults based on temporal data. The LSTM outputs are incorporated into the EKF as pseudo-measurements with adaptive covariance tuning, ensuring stability and robustness.* ***Results.*** *Simulation results demonstrate that the hybrid EKF–LSTM reduces trajectory root mean square error (RMSE) by 4.6 % and fault RMSE by 68 % compared to a standalone EKF, and by more than 50 % compared to the UKF. The framework effectively tracks abrupt fault variations and remains resilient to unknown inputs and sensor noise.* ***Scientific novelty.*** *Unlike existing hybrid filters, the proposed method introduces adaptive covariance fusion between EKF and LSTM estimators, enabling reliable operation under directional dynamics and unmodeled disturbances.* ***Practical value.*** *The proposed hybrid EKF–LSTM framework enhances fault-tolerant localization for autonomous robots, providing a scalable solution for real-time applications such as search-and-rescue operations, industrial automation, and autonomous navigation in noisy or GPS-denied environments.* References 33, tables 2, figures 5.

Key words: **mobile robotics, fault-tolerant localization, extended Kalman filter, long short-term memory, hybrid estimation, unknown disturbances.**

Вступ*. Надійне та точне оцінювання стану відіграє ключову роль у мобільній робототехніці, забезпечуючи ефективну локалізацію, навігацію та керування в невизначених і динамічних середовищах. Традиційні методи оцінювання, такі як розширений фільтр Калмана (EKF) та незсунений фільтр Калмана (UKF), широко застосовуються для нелінійних систем; однак їх ефективність знижується за наявності невідомих збурень або похибок моделювання.* ***Проблема****. У реальних мобільних роботах несподівані відмови двигунів і невимірювані збурення суттєво знижують точність оцінювання та можуть призводити до зриву виконання завдання. Класичні підходи EKF і UKF базуються на статичних моделях і припущенні гаусівського шуму, що робить їх малопридатними для систем із невідомими або змінними в часі невизначеностями.* ***Метою*** *роботи є розроблення та валідація гібридної структури розширеного фільтра Калмана з довгою короткостроковою пам'яттю (EKF–LSTM), здатної забезпечити одночасне оцінювання стану та відмов мобільних роботів в умовах невідомих збурень.* ***Методика****. Запропонований підхід поєднує модельно-орієнтований EKF із нейронною мережею LSTM, навченою офлайн. EKF виконує нелінійне оцінювання стану на основі фізичної моделі руху робота та зашумлених вимірювань глобальної системи позиціонування (GPS), тоді як LSTM прогнозує адитивні відмови двигунів на основі часових даних. Виходи LSTM інтегруються в EKF як псевдовимірювання з адаптивним налаштуванням коваріації, що забезпечує стійкість і робастність алгоритму.* ***Результати*** *моделювання показали, що гібридний підхід EKF–LSTM зменшує середньоквадратичну похибку траєкторії (RMSE) на 4,6 % та похибку оцінювання відмов на 68 % порівняно з окремим EKF і більш ніж на 50 % порівняно з UKF. Запропонована структура ефективно відстежує різкі зміни відмов і зберігає стійкість до невідомих впливів і шумів сенсорів.* ***Наукова новизна****. На відміну від існуючих гібридних фільтрів, запропонований метод передбачає адаптивне узгодження коваріацій між оцінювачами EKF і LSTM, що забезпечує надійну роботу за наявності спрямованої динаміки та немодельованих збурень.* ***Практична значимість****. Запропонована гібридна структура EKF–LSTM підвищує ефективність відмовостійкої локалізації автономних роботів і може бути масштабована для застосувань у реальному часі, зокрема в пошуково-рятувальних операціях, промисловій автоматизації та автономній навігації в умовах шумів або відсутності сигналу GPS.* Бібл. 33, табл. 2, рис. 5.

Ключові слова: **мобільна робототехніка, відмовостійка локалізація, розширений фільтр Калмана, довга короткострокова пам'ять, гібридне оцінювання, невідомі збурення.**

Introduction. Reliable state estimation is fundamental in mobile robotics, serving as the backbone for navigation, control, and fault-tolerant decision-making in uncertain environments [1, 2]. Mobile robots often operate in dynamic conditions where sensor measurements are noisy [3] and process models are affected by unmodeled dynamics, disturbances, and faults [4, 5]. Among these, actuator and motor faults are particularly critical, as they may lead to performance degradation, unsafe behavior, or even mission failure if not properly detected and compensated [6, 7]. Recent advances in sensor fusion and adaptive filtering have further highlighted the need for robust state estimation in global positioning system (GPS)-denied or highly dynamic environments [8, 9].

To address these challenges, model-based estimation methods have been extensively studied. The extended Kalman filter (EKF) is one of the most widely used tools for nonlinear state estimation in robotics [10], while high-order extensions [11] and unscented Kalman filter (UKF) approaches [12] improve estimation accuracy by better approximating nonlinear dynamics. These methods provide reliable estimates under Gaussian noise assumptions, but their performance can degrade in the presence of unknown inputs, strong nonlinearities, or unexpected faults [13, 14]. Recent works have also explored adaptive variants to handle complex nonlinearities and uncertainties [15]. Intelligent observers, such as fuzzy back-stepping designs for induction motors, have shown robust nonlinear sensor less state estimation capabilities [16], demonstrating the complementarity between model-based and intelligent approaches.

In parallel, research on fault detection and isolation (FDI) has highlighted the importance of estimating not only the state, but also faults in real time. Model-based fault detection techniques rely on residual generation and adaptive observers [17], while robust fault-tolerant control strategies have been designed to mitigate the impact of actuator and sensor faults, such as those based on multiple-constraint Takagi-Sugeno approaches for permanent magnet synchronous machines [18–20]. However, explicit fault modeling remains challenging when fault dynamics are uncertain or when disturbances mimic fault signatures [21]. Distributed and interacting multiple model approaches have also been proposed to enhance fault diagnosis in multi-sensor robotic systems [22]. Data-driven approaches, including artificial neural networks for fault diagnosis in photovoltaic systems, have further illustrated the potential of learning-based methods to capture complex system behaviors [23].

In recent years, data-driven approaches based on deep learning have emerged as powerful alternatives. Long short-term memory (LSTM) networks [24] have shown remarkable ability to capture long-term dependencies in time-series data, leading to successful applications in predictive maintenance and fault prognosis [25]. Recent works have also demonstrated the effectiveness of hybrid EKF–LSTM models in estimating dynamic states in noisy and uncertain environments, particularly for applications such as battery state-of-charge estimation [26] and photovoltaic system parameter estimation [27]. Despite their predictive power, purely data-driven methods often lack physical interpretability and may fail when faced with unseen scenarios [28].

To overcome the limitations of traditional model-based or data-driven methods, recent studies have explored hybrid approaches that combine the interpretability of physical models with the flexibility of neural networks. Attention mechanisms [29] and multi-sensor fusion frameworks [30] have been employed to improve robustness in complex environments, demonstrating enhanced adaptability and accuracy [31, 32]. Building on this trend, in [33] was proposed a hybrid EKF–LSTM approach for state and fault estimation in mobile robots, highlighting the benefits of integrating deep learning with Kalman filtering. However, that study did not explicitly address adaptive covariance tuning or the handling of unknown disturbances challenges that the present work addresses by introducing an adaptively fused EKF–LSTM framework capable of managing directional dynamics and sensor uncertainties.

Review of the literature. State estimation and fault detection are critical components in the fields of robotics, autonomous systems, and electrical engineering. Traditional methods, such as the EKF and UKF, have been widely applied for state estimation in nonlinear systems. Work [10] provided a comprehensive review of sigma-point Kalman filters, emphasizing their effectiveness in sensor fusion and state estimation. In [11] were explored high-order EKFs to enhance the accuracy of state estimation in nonlinear systems.

FDI are essential for ensuring the reliability and safety of robotic and electrical systems. Research [17] presented robust approaches for multiple fault detection and estimation in nonlinear systems, while surveyed model-based methods for fault-tolerant control in mobile robots. The study [19] utilized robust relative navigation techniques for fault-tolerant control, addressing the challenges posed by uncertain fault dynamics and disturbances. Work [21] focused on the evaluation of uncertainties for state estimation with the Kalman filter, including unknown inputs and disturbances, further emphasizing the need for robust state estimation techniques.

Recent advancements have seen the integration of data-driven techniques, such as LSTM networks, with traditional model-based methods to improve state estimation and fault detection. In [24] were introduced LSTM networks for modeling temporal sequences, which have since been widely adopted for fault diagnosis and prognosis. In [25] was demonstrated the effectiveness of LSTM networks in robust inertial navigation. Works [26–28] proposed hybrid approaches combining LSTM and EKF for robust state and fault estimation in mobile robots under dynamic noise environments, showcasing the potential of integrating deep learning with traditional filtering techniques.

Hybrid approaches that combine the strengths of model-based filters and data-driven learning have recently attracted significant attention for localization, sensor fusion, and fault detection tasks. In [29] was discussed a multi-sensor decision-level fusion network based on attention mechanisms for object detection, highlighting the importance of adaptive and robust sensor fusion strategies. Work [31] proposed an adaptive feature fusion strategy using dual-layer attention and multi-modal deep reinforcement learning, demonstrating the benefits of integrating neural networks with traditional estimation frameworks. In [32] was introduced a hybrid CWT–ResNet–LSTM model for bearing fault diagnosis, showcasing the potential of deep learning architectures in fault detection and classification.

Previous work [33] introduced a hybrid EKF–LSTM framework for robust state and fault estimation in mobile robots, demonstrating the potential of coupling deep learning with EKF for enhanced robustness under dynamic noise conditions. However, that study did not explicitly address adaptive covariance tuning or the management of unknown disturbances aspects that the present work aims to improve through an adaptively fused EKF–LSTM scheme capable of handling directional dynamics and sensor uncertainty.

Despite these advancements, effectively integrating deep learning with traditional state estimation remains challenging. To address this, we propose a hybrid EKF–LSTM framework that combines model-based filtering with LSTM-based fault prediction.

The **goal** of this work is to design and validate a hybrid EKF–LSTM framework capable of achieving joint state and fault estimation for mobile robots operating under unknown disturbances. The proposed approach aims to combine the model-based accuracy of the EKF with the data-driven predictive power of LSTM networks, by incorporating LSTM-based fault predictions as pseudo-measurements within the EKF through adaptive covariance tuning. This integration seeks to enhance the system's robustness against sensor noise and disturbances, while improving estimation accuracy and fault detectability in dynamic environments.

Problem formulation. Accurate modeling of the mobile robot dynamics and measurement process is essential for robust state and fault estimation. In this section, we define the nonlinear robot model, the fault and disturbance representation, and the measurement model, which will serve as the foundation for the estimation framework. The formulation explicitly considers unknown external disturbances and actuator faults, which are common in real-world mobile robotic systems.

Mobile robot model. The mobile robot is modeled with nonlinear kinematics in a 2D plane. The state vector is defined as:

$$x_{k+1} = f(x_k) + w_{x,k}, \tag{1}$$

where $x_k = [X_k, Y_k, \theta_k, f_{v,k}]^T$, X_k and Y_k, are the position; θ_k is the heading angle; $f_{v,k}$ is the additive motor fault affecting the robot's forward velocity; $w_{x,k}$ is the zero-mean Gaussian measurement noise.

The control inputs consist of the commanded forward velocity v_c and angular velocity ω_c. Additionally, the robot is subject to unknown external disturbances: d_v on velocity and d_θ on orientation. The discrete-time dynamics of the robot are given by:

$$X_{k+1} = X_k + (v_{c,k} + f_{v,k} + d_{v,k})\cdot\cos(\theta_k)\Delta t; \tag{2}$$

$$Y_{k+1} = Y_k + (v_{c,k} + f_{v,k} + d_{v,k})\cdot\sin(\theta_k)\Delta t; \tag{3}$$

$$\theta_{k+1} = \theta_k + (\omega_{c,k} + d_{\theta,k})\cdot\Delta t; \tag{4}$$

$$f_{v,k+1} = f_{v,k}, \tag{5}$$

where Δt is the sampling interval. The fault $f_{v,k}$ is assumed slowly varying and additive, capturing actuator degradation or motor faults.

Measurement model. The robot is equipped with a GPS-like sensor providing noisy position measurements:

$$z_k = \begin{bmatrix} X_k \\ Y_k \end{bmatrix} + v_k, \tag{6}$$

where v_k is the zero-mean Gaussian measurement noise.

In addition, a pseudo-measurement of the fault will later be introduced via an LSTM-based predictor, which provides an estimate of $f_{v,k}$ using historical sensor data and EKF state estimates. In summary, the mobile robot dynamics are modeled as a nonlinear discrete-time system with an augmented state vector that includes position, orientation, and an additive motor fault. Noisy GPS measurements provide partial observations of the state, while unknown disturbances in velocity and orientation remain unmeasured. This problem formulation highlights the challenges of joint state and fault estimation under realistic conditions.

Estimation method. Accurate estimation of both the robot states and the motor fault under unknown disturbances requires a combination of model-based and data-driven methods. In this work, we propose a hybrid EKF–LSTM framework, where the EKF provides a principled model-based estimate using the nonlinear robot dynamics and GPS measurements, while the LSTM captures temporal patterns and predicts the fault from historical sensor data. The two components are fused online via an adaptive Kalman update, improving robustness against unknown disturbances and sensor noise.

Figure 1 provides a schematic overview of the proposed hybrid approach. It illustrates the data flow and the interaction between the model-based EKF and the data-driven LSTM, highlighting how the hybrid framework combines predictions from the robot's nonlinear dynamics with LSTM-based fault estimates to achieve robust state and fault estimation under unknown disturbances.

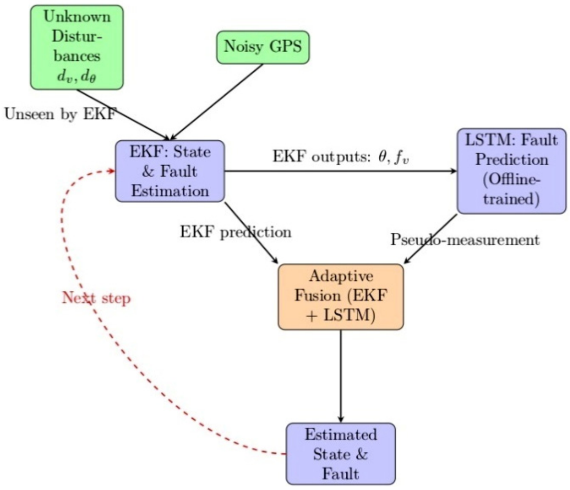

Fig. 1. System architecture of the hybrid EKF–LSTM estimator

EKF-based state and fault estimation. The EKF estimates both the robot states and the additive motor fault. The augmented state vector is:

$$x_k = \begin{bmatrix} X_k \\ Y_k \\ \theta_k \\ f_{v,k} \end{bmatrix}, \tag{7}$$

The nonlinear dynamics are used to predict the next state:

$$\hat{x}_{k|k-1} = f\left(\hat{x}_{k-1|k-1}\right). \tag{8}$$

The EKF linearizes the nonlinear dynamics using the state transition Jacobian $F_{k-1} = \partial f / \partial x_k$:

$$F_{k-1} = \begin{bmatrix} 1 & 0 & v_{eff}\sin(\theta_k)\Delta k & \cos(\theta_k)\Delta k \\ 0 & 1 & v_{eff}\cos(\theta_k)\Delta k & \sin(\theta_k)\Delta k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{9}$$

where $v_{eff} = v_{c,k} + f_{v,k}$. This captures the influence of the fault and orientation on position updates.

The measurement Jacobian $H_k = \partial h / \partial x_k$ for GPS measurements is:

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}. \tag{10}$$

Covariance prediction and update:

$$P_{k|k-1} = F_{k-1}P_{k-1|k-1}F_{k-1}^T + Q_{k-1}; \tag{11}$$

$$K_k = P_{k|k-1}H_k^T\left(H_k P_{k|k-1}H_k^T + R_k\right)^{-1}; \tag{12}$$

$$\hat{x}_{k|k=}\hat{x}_{k|k-1} + K_k\left(z_k - h\left(\hat{x}_{k|k-1}\right)\right); \tag{13}$$

$$P_{k|k} = \left(I - K_k H_k\right)P_{k|k-1}. \tag{14}$$

This EKF provides a baseline estimation of both the robot state and the fault without requiring knowledge of the unknown disturbances. However, the presence of unmodeled inputs, such as velocity and orientation perturbations ($d_{v,k}$ and $d_{\theta,k}$), can bias the state and fault estimates and increase estimation uncertainty, motivating the integration of a data-driven LSTM predictor to compensate for these unknown effects.

LSTM-based fault estimation. A LSTM network is employed to predict the fault $f_{v,k}$ based on historical measurements and EKF estimates. The LSTM captures temporal dependencies in the sensor data and the dynamics of the fault. Let the input feature vector at time step k be:

$$\hat{x}_k = \begin{bmatrix} \hat{X}_k^{EKF} \\ \hat{Y}_k^{EKF} \\ \hat{\theta}_k^{EKF} \\ \hat{f}_{v,k}^{EKF} \end{bmatrix}. \quad (15)$$

Using a lookback window of length L, the LSTM input sequence is:

$$x_k = [x_{k-L+1}, x_{k-L+2}, \dots , x_k]. \quad (16)$$

The LSTM computes the hidden states h_t and cell states C_t recursively at each time step t within the window:

$$\begin{gathered} i_t = \sigma(W_i \times x_t + U_i h_{t-1} + b_i); \\ f_t = \sigma(W_f \times x_t + U_f h_{t-1} + b_f); \\ o_t = \sigma(W_o \times x_t + U_o h_{t-1} + b_o); \\ \widetilde{C}_t = \tanh(W_c \times x_t + U_c h_{t-1} + b_c); \\ C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t; \\ h_t = o_t \odot \tanh(C_t), \end{gathered} \quad (17)$$

where x_t is the input at time t; h_t is the hidden state vector; C_t is the cell state vector; f_t, i_t and o_t are the forget, input and output gates respectively; σ is the sigmoid activation function; W, U and b are the learnable LSTM weights.

The final hidden state is passed through a dense layer to predict the fault:

$$\hat{f}_{v,k}^{LSTM} = W_y h_k + b_y. \quad (18)$$

The specific LSTM parameters (lookback length, number of hidden units, activation functions, optimizer, etc.) are detailed in the Simulation section to provide reproducibility.

This output generates a pseudo-measurement for the fault, which can be integrated into the EKF to enhance estimation accuracy. In the next subsection, we present the hybrid EKF–LSTM fusion framework, where the LSTM output is adaptively fused with the EKF state estimate to jointly improve state and fault estimation in the presence of unknown disturbances.

Hybrid EKF–LSTM fusion. To improve fault estimation accuracy and robustness against unknown disturbances, the proposed framework integrates model-based EKF estimates with data-driven LSTM predictions. EKF provides a physically consistent state estimate, while the LSTM captures complex temporal patterns in fault evolution that are difficult to model analytically. By fusing these two sources, the hybrid approach leverages the complementary strengths of model-based and learning-based methods.

After the EKF GPS update, the LSTM pseudo-measurement is incorporated:

$$\tilde{y}_k^{LSTM} = \hat{f}_{v,k}^{LSTM} - \hat{f}_{v,k}^{EKF}; \quad (19)$$

$$S_k^{LSTM} = H_{LSTM} P_{k|k} H_{LSTM}^T + R_{LSTM}; \quad (20)$$

$$K_k^{LSTM} = P_{k|k} H_{LSTM}^T \left(S_k^{LSTM}\right)^{-1}; \quad (21)$$

$$\hat{x}_{k|k}^{Fused} = \hat{x}_{k|k}^{EKF} + K_k^{LSTM} \tilde{y}_k^{LSTM}; \quad (22)$$

$$P_{k|k}^{Fused} = \left(I - K_k^{LSTM} H_{LSTM}\right) P_{k|k}, \quad (23)$$

where H_{LSTM} = [0, 0, 0, 1] selects the fault component; R_{LSTM} is adaptively estimated from the recent variance of $\left(\hat{f}_{v,k}^{LSTM} - \hat{f}_{v,k}^{EKF}\right)$. This adaptive covariance ensures stability and prevents overconfidence in LSTM predictions.

The hybrid EKF–LSTM fusion provides an enhanced estimation of the motor fault compared to using either EKF or LSTM alone. The adaptive covariance tuning ensures that the filter remains stable and robust to variations in LSTM prediction accuracy. This approach allows the framework to effectively handle unknown disturbances, improving overall state and fault estimation performance in dynamic and noisy environments.

Simulation results and performance analysis. To validate the effectiveness of the proposed hybrid EKF–LSTM framework, a set of numerical simulations is conducted on a mobile robot model subject to unknown disturbances and additive motor faults. The simulations aim to reproduce realistic operating conditions where classical model-based estimation may be degraded due to unmodeled dynamics and noisy sensor measurements. The experimental setup includes the generation of the robot's ground-truth trajectory, noisy GPS observations, motor fault injection, and external perturbations on both velocity and orientation. The performance of the proposed hybrid estimator is then compared against conventional approaches, namely the EKF without LSTM augmentation and the LSTM-based fault prediction alone. In addition, the UKF is included as a benchmark to assess whether nonlinear filtering offers advantages over the EKF in this scenario.

Simulation framework and parameters. The robot's motion is modeled kinematically under constant control inputs, maintaining a steady linear velocity of v_c = 2 m/s and a steady angular velocity of ω_c = 0.1 rad/s. The simulation environment is designed to emulate the motion of a mobile robot subject to noisy measurements, additive motor faults, and unknown disturbances. The discrete-time simulation runs for n = 200 steps with a sampling interval of Δt = 0.1 s, corresponding to a total duration of 20 s (Fig. 2).

The process noise and measurement noise are modeled as Gaussian with covariance matrices:

$$Q_{x,k} = \text{diag}(0.005; 0.005; 0.0005); \; R_k = \text{diag}(0.05; 0.05).$$

The initial state of the robot and covariance matrix are set to:

$$x_0 = [0; 0; \pi/4; 0]^T; \; P_0 = \text{diag}(0.1; 0.1; 0.1; 0.01).$$

An additive motor fault is introduced in the velocity channel. It evolves as a slowly varying bias with an abrupt increase at mid-simulation ($k \geq 100$) to emulate a sudden motor degradation:

$$f_{v,k} = 0.002k + \Delta f(k) + w_{f,k},$$

where $\Delta f(k)$ is the abrupt fault increment at step k=100; $w_{f,k}$ is the Gaussian noise with covariance matrix $Q_{f,k}$ = 0.02.

To capture realistic operating conditions, two unmodeled disturbances are applied (see Fig. 3):

- velocity disturbance: $d_{v,k} = 0.1\sin(2\pi \cdot 0.01 \cdot k\Delta t)$;
- orientation disturbance: $d_{\theta,k} \sim N(0, 0.05)$,

where the former represents smooth oscillations (e.g., due to uneven terrain), and the latter is a random perturbation (e.g., steering noise). In addition to the EKF, a LSTM network is trained to predict the additive motor fault based on past system states and control inputs. The LSTM is structured with:

- Input sequence length: 10 past steps.
- One hidden layer with 64 LSTM units.
- Dropout regularization with a rate of 0.2 to prevent overfitting.
- Fully connected output layer mapping the hidden state to the predicted fault $\hat{f}_{v,k}$.
- Training setup: Adam optimizer, learning rate 10^{-3}, and mean squared error (MSE) loss.

The LSTM output is used as a pseudo-measurement of the fault, which is dynamically fused with the EKF estimate via the adaptive weighting mechanism.

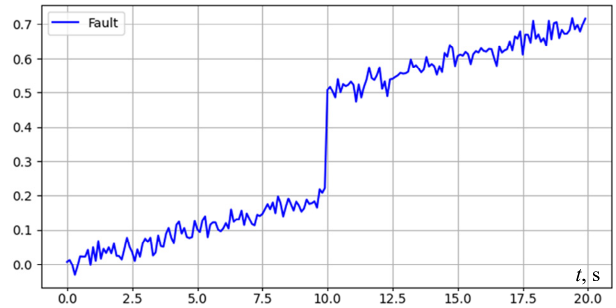

Fig. 2. True fault generation

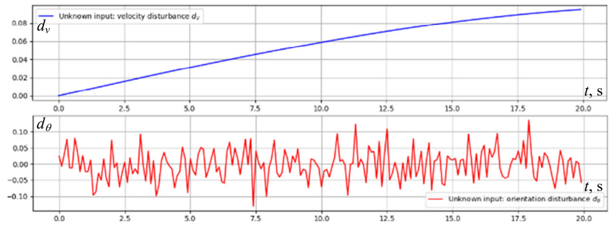

Fig. 3. Real unknown disturbances $d_{v,k}$ and $d_{\theta,k}$

Trajectory estimation. The first validation of the proposed framework is performed through trajectory estimation under the simulated noisy and faulty conditions. The objective is to evaluate whether the hybrid EKF–LSTM estimator can accurately track the robot's trajectory while simultaneously compensating for additive motor faults and disturbances. Figure 4 shows the ground-truth trajectory compared to the estimates obtained with 3 approaches: the conventional EKF, the UKF and the proposed hybrid EKF–LSTM.

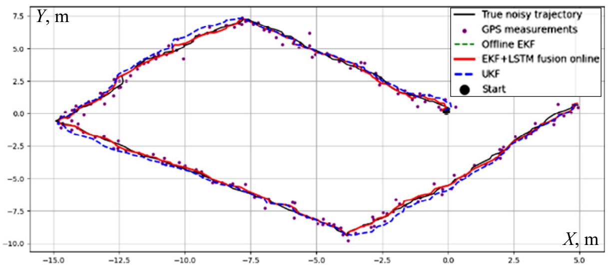

Fig. 4. Trajectory estimation

Figure 4 compares the estimated robot trajectories using the EKF, UKF and the proposed EKF–LSTM hybrid fusion against the true noisy trajectory and GPS measurements. The GPS-only localization (purple points) is highly scattered due to sensor noise.

- EKF (green dashed line) significantly improves trajectory reconstruction and closely follows the ground truth path. Its Jacobian-based linearization proves sufficiently accurate given the moderate nonlinearity of the kinematic model, and it demonstrates robustness against the injected disturbances.
- By contrast, UKF (blue dashed line) provides less accurate estimates in this scenario. While the UKF theoretically captures nonlinear effects more effectively, the presence of unmodeled disturbances distorts the sigma-point propagation. This results in inflated uncertainty and noticeable trajectory deviations, particularly during turns. Consequently, EKF surpasses UKF in this setup.
- Hybrid EKF–LSTM fusion (red line) delivers the best overall performance. The LSTM component learns disturbance and fault patterns from historical data, compensating for model mismatch, while the EKF ensures dynamical consistency. This synergy achieves the most accurate trajectory reconstruction under noisy and disturbed conditions.

The root mean square error (RMSE) and the mean absolute error (MAE) between the estimated and true trajectories are used as performance indicators:

$$RMSE_{pos} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(\left(X_k - \hat{X}_k\right)^2 + \left(Y_k - \hat{Y}_k\right)^2\right)};$$

$$MAE_{pos} = \frac{1}{n}\sum_{k=1}^{n}\sqrt{\left(\left(X_k - \hat{X}_k\right)^2 + \left(Y_k - \hat{Y}_k\right)^2\right)}.$$

Numerical results, presented in Table 1, highlight the following trends:

- EKF provides competitive trajectory estimation with an RMSE of 0.182 and MAE of 0.162. Its performance remains relatively robust despite the presence of unknown inputs, which can significantly disturb the system dynamics.
- UKF exhibits higher errors, with an RMSE of 0.372 and MAE of 0.321, indicating that sigma-point propagation is less effective in mitigating the impact of unknown inputs in this scenario.
- Hybrid EKF–LSTM achieves the lowest errors, with an RMSE of 0.174 and MAE of 0.154. By integrating LSTM predictions, the framework can better capture the effects of unknown inputs and unmodeled dynamics, resulting in an improvement of ~4.6 % over EKF and more than 50 % over UKF.

In summary, the results in Fig. 4 and Table 1 show that while EKF can outperform UKF when disturbances dominate, unknown disturbances still challenge traditional filters. The hybrid EKF–LSTM framework consistently provides the most accurate and robust trajectory estimation by effectively accounting for these unknown disturbances.

Table 1

Comparative performance metrics for trajectory estimation

Metric	EKF	UKF	EKF–LSTM
RMSE	0.182	0.372	0.174
MAE	0.162	0.321	0.154

Fault estimation. In addition to trajectory reconstruction, a key objective of this study is the accurate estimation of the additive motor fault affecting the mobile robot. The fault signal is modeled as an unknown disturbance added to the control input, and its estimation is essential for both robust state estimation and early fault detection.

Figure 5 presents the estimation of the additive motor fault obtained with EKF, UKF, LSTM-only prediction, and the proposed EKF–LSTM fusion framework, compared to the true injected fault:

- EKF (green dashed line) successfully captures the general evolution of the fault, including both the slow drift and the abrupt jump around t = 10 s. However, the estimates exhibit oscillations and noticeable variance due to the influence of unknown disturbances and measurement noise.
- UKF (blue dashed line), contrary to expectations, performs poorly in this case. Its sigma-point propagation is highly sensitive to unmodeled disturbances, resulting in large deviations from the true fault and even sign inconsistencies during certain intervals. This confirms that the UKF does not provide robustness advantages under disturbance-dominated dynamics.
- Hybrid EKF–LSTM fusion framework (red line) achieves the most accurate and stable fault estimation. By dynamically combining EKF's model-based consistency with the LSTM's ability to learn and predict fault patterns, the fusion reduces estimation lag and smoothes oscillations. The abrupt fault jump is captured with high precision, while maintaining robustness against disturbances throughout the simulation.

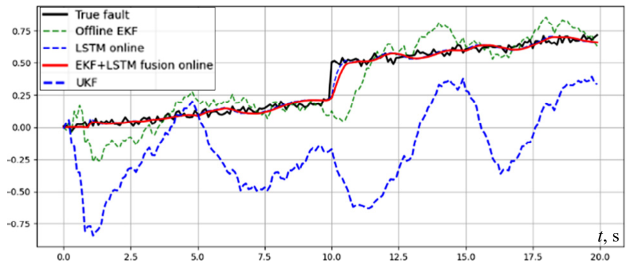

Fig. 5. Fault estimation

The estimation error of the fault is evaluated using the RMSE and the MAE:

$$RMSE_{fault} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(f_{v,k} - \hat{f}_{v,k}\right)^2}\ ;$$

$$MAE_{fault} = \frac{1}{n}\sum_{k=1}^{n}\left|f_{v,k} - \hat{f}_{v,k}\right|.$$

Simulation results, summarized in Table 2, indicate the following trends:

- EKF provides reasonably accurate fault estimation with an RMSE of 0.138 and MAE of 0.101. However, its performance is limited by unknown inputs and abrupt nonlinear disturbances, which can perturb the fault estimation.
- UKF performs significantly worse, with an RMSE of 0.604 and MAE of 0.528, showing that sigma-point propagation is not sufficient to handle unknown inputs or rapid fault dynamics in this scenario.
- Hybrid EKF–LSTM achieves the lowest errors, with an RMSE of 0.044 and MAE of 0.030, corresponding to a ~68 % improvement over EKF and more than 90 % over UKF. By incorporating LSTM predictions, the framework effectively captures the effects of unknown inputs and unmodeled dynamics, enabling accurate and real-time fault estimation.

As illustrated in Fig. 5 and Table 2, the hybrid framework achieves near-perfect alignment with the true injected fault, even during abrupt transitions. In contrast, EKF and UKF both underestimate the fault magnitude and exhibit delayed convergence, emphasizing the challenges posed by unknown inputs. These results highlight the hybrid EKF–LSTM method's superior capability for real-time FDI in mobile robots operating under unknown disturbances.

Table 2

Comparative performance metrics for fault estimation

Variable	Metric	EKF	UKF	EKF–LSTM
$f_{v,k}$	RMSE	0.138	0.604	0.044
	MAE	0.101	0.528	0.030

Conclusions. In this paper, we proposed a hybrid EKF–LSTM framework for robust joint state and fault estimation in mobile robots operating under unknown disturbances. The approach combines an augmented EKF, which jointly estimates the robot state and additive motor fault, with an offline-trained LSTM providing pseudo-measurements for the fault. The fusion is performed with adaptive covariance tuning, ensuring stable and accurate estimation even in the presence of unmodeled disturbances. Simulation results show that the hybrid framework outperforms standard EKF and UKF, achieving lower RMSE and MAE for both trajectory (~4–5 % improvement over EKF, 50 % over UKF) and fault estimation (~68 % over EKF, 90 % over UKF). It accurately tracks abrupt fault changes and remains robust against unknown inputs, demonstrating its potential for real-time FDI in robotic applications.

Future work will extend this approach to multi-robot systems, explore gated recurrent unit and transformer-based predictors, validate on physical platforms, and develop adaptive FDI strategies for complex environments.

Conflict of interest. The authors declare that they have no conflicts of interest.

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Received 16.10.2025
Accepted 21.12.2025
Published 02.05.2026

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How to cite this article:
Khemiri K., Djebali R. Hybrid extended Kalman filter long short-term memory framework for robust state and fault estimation in mobile robots under unknown disturbances. *Electrical Engineering & Electromechanics*, 2026, no. 3, pp. 55-61. doi: https://doi.org/10.20998/2074-272X.2026.3.08