

EDGE Method for Identification and Prediction of Dynamic Object Trajectories for a Mobile Robot Based on YOLO26n

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Abstract: This paper proposes an EDGE method for the identification and trajectory prediction of dynamic objects for a mobile robot based on YOLO26n, which integrates local object detection, estimation of object positions and motion parameters, short-term trajectory prediction, and assessment of potential collision risk. The numerical simulation results confirmed the operability of the proposed method: the successful detection rate reached 96.68%, the position estimation RMSE after filtering was 0.0470m, and the trajectory prediction RMSE for a 2.0s prediction horizon was 0.3193m. The obtained results demonstrate the potential of the proposed method for local analysis of dynamic environments and early detection of potentially hazardous interactions between a mobile robot and moving objects.

Keywords: EDGE Computing, YOLO26n, mobile robot, object identification, dynamic objects, trajectory prediction.

I. INTRODUCTION

The rapid development of autonomous mobile robots and their application in dynamic environments necessitate the development of highly efficient methods for the local identification of moving objects, estimation of their motion parameters, and real-time prediction of possible trajectories. The use of EDGE Computing technology in combination with the YOLO26n neural network model enables video stream processing directly on the onboard computing platform of a mobile robot, thereby reducing data transmission latency and the dependence of the control system on external cloud resources. Of particular relevance is not only the identification of dynamic objects but also the estimation of their velocity and direction of motion, followed by short-term trajectory prediction, which enables early assessment of potential collision risks and adaptation of the robotic platform's motion. Therefore, the development of an EDGE Method for Identification and Trajectory Prediction of Dynamic Objects for a Mobile Robot Based on YOLO26n is a relevant scientific and applied task aimed at improving the autonomy, computational responsiveness, and operational safety of mobile robotic systems in dynamic working environments.

II. DEVELOPMENT OF THE EDGE METHOD FOR IDENTIFICATION AND TRAJECTORY PREDICTION

To ensure the autonomous operation of a mobile robot in a dynamic environment, it is necessary to implement sequential detection of moving objects, determination of their motion parameters, and prediction of their future positions directly on the onboard EDGE platform. The proposed EDGE method involves processing a sequence of video frames to generate data on the object class,

coordinates, and detection confidence, which are subsequently used to estimate its dynamic state and predict its motion trajectory. The initial stage of the method involves local detection and determination of the spatial position of objects in the current frame, which is described by the YOLO26n-based EDGE model for dynamic object identification.

YOLO26n-Based EDGE Model for Dynamic Object Identification. At the first stage, the video frame acquired by the mobile robot's camera is processed locally on the EDGE device using the YOLO26n model. For each detected object, the following vector is formed:

$$\begin{aligned} D_{i,t} &= [c_i, p_{i,t}, x_{i,t}, y_{i,t}, w_{i,t}, h_{i,t}] \\ D_i &= NMS(f_{YOLO26n}(I_t; \Theta), \tau_c, \tau_{IoU}) \end{aligned} \quad (1) \quad (2)$$

de: I_t - the current video frame at time t ; $f_{YOLO26n}$ - YOLO26n inference function; Θ - neural network parameters; c_i - class of the i -th object; $p_{i,t}$ - detection confidence; $x_{i,t}, y_{i,t}$ - bounding box center coordinates; $w_{i,t}, h_{i,t}$ - its width and height; τ_c - minimum threshold confidence; τ_{IoU} - IoU threshold for NMS.

Models 1–2 describe the local identification and determination of the spatial position of dynamic objects without transmitting the video stream to a cloud system..

Object State and Motion Parameter Estimation Model. For trajectory prediction, determining only the object's position is insufficient. Therefore, a dynamic state vector is formed for each object::

$$X_{i,t} = [x_{i,t}, y_{i,t}, v_{x,i,t}, v_{y,i,t}]^T \quad (3)$$

where the velocity components can be determined from a sequence of detections:

$$v_{x,i,t} = \frac{x_{i,t} - x_{i,t-1}}{\Delta t}, \quad v_{y,i,t} = \frac{y_{i,t} - y_{i,t-1}}{\Delta t} \quad (4)$$

The velocity magnitude and direction of motion are determined as follows:

$$\begin{aligned} v_{i,t} &= \sqrt{v_{x,i,t}^2 + v_{y,i,t}^2}, & \varphi_{i,t} &= \text{atan2}(v_{y,i,t}, v_{x,i,t}) \end{aligned} \quad (5)$$

de: $x_{i,t}, y_{i,t}$ - current coordinates of the object center; $x_{i,t-1}, y_{i,t-1}$ - coordinates in the previous frame; Δt - time

interval between frames; $v_{x,i,t}, v_{y,i,t}$ - velocity components; $v_{i,t}$ - estimated velocity; $\varphi_{i,t}$ - direction of motion.

Models 3–5 transform the results of sequential YOLO26n detections into the motion parameters of a dynamic object required to predict its future position.

The Dynamic Object Trajectory Prediction Model is designed for short-term EDGE-based prediction and can employ a constant-velocity kinematic model that does not require significant computational resources.:

$$\hat{\mathbf{P}}_i(t + \tau) = \begin{bmatrix} \hat{x}_i(t + \tau) \\ \hat{y}_i(t + \tau) \end{bmatrix} = \begin{bmatrix} x_{i,t} + v_{x,i,t}\tau \\ y_{i,t} + v_{y,i,t}\tau \end{bmatrix} \quad (6)$$

Accordingly, the predicted trajectory is defined by the following set:

$$\hat{\mathbf{r}}_i = \{\hat{\mathbf{P}}_i(t + \tau_k)\}_{k=1}^{N_p} \quad (7)$$

де: $\hat{x}_i, \hat{y}_i$ - predicted object coordinates; τ - prediction horizon from the current time instant; N_p - number of predicted points; $\hat{\mathbf{r}}_i$ - predicted trajectory of the i -th object.

Models 6–7 describe the short-term prediction of the future position of a detected object without using computationally intensive LSTM/Transformer models, which is particularly important for Raspberry Pi and other EDGE platforms..

The Mobile Robot–Dynamic Object Collision Risk Assessment Model is designed to directly relate the predicted trajectory to the motion safety of the mobile robot. The minimum predicted distance between the robot trajectory $\mathbf{P}_R$ and the object is determined as follows.:

$$d_i^{min} = \min_{\tau \in [0, T_p]} \|\hat{\mathbf{P}}_i(t + \tau) - \hat{\mathbf{P}}_R(t + \tau)\|_2 \quad (8)$$

Then, the normalized risk indicator can be expressed in a compact form as follows.:

$$R_i = p_{i,t} \exp\left(-\frac{d_i^{min}}{d_s}\right), 0 \leq R_i \leq 1 \quad (9)$$

and the overall risk for the mobile robot:

$$R(t) = \max_i R_i \quad (10)$$

Де: d_i^{min} - minimum predicted distance between the robot and the i -th object; $\hat{\mathbf{P}}_R$ - predicted position of the mobile robot; d_s - specified safe distance; $p_{i,t}$ - confidence YOLO26n; R_i - risk associated with a specific object; $R(t)$ - maximum current collision risk.

Models 8–10 enable the transformation of trajectory prediction results into a quantitative risk indicator, which can subsequently be used by the control system to reduce speed, apply braking, or modify the trajectory of the mobile robot.

III. NUMERICAL MODELING AND ANALYSIS OF THE OBTAINED RESULTS

The purpose of the numerical simulation is to verify the operability and adequacy of the developed EDGE method for the identification and trajectory prediction of dynamic objects for a mobile robot based on YOLO26n under conditions of changes in the object's velocity and direction of motion, the presence of identification errors, and possible short-term missed detections. The expected simulation results include stable identification and estimation of the coordinates and velocity of a dynamic object, short-term prediction of its trajectory, and timely assessment of the potential collision risk with the mobile robot, while the adequacy of the method is evaluated using position RMSE and MAE, velocity RMSE, trajectory prediction RMSE and MAE, the successful detection rate, and the minimum predicted distance. The simulation is performed over a period of 30 s with a time step of 0.1 s, a prediction horizon of 2.0 s, and a prediction step of 0.1 s; to simulate YOLO26n detection results, a confidence threshold of 0.50, a coordinate error standard deviation of 0.045 m, and a missed-detection probability of 0.03 are used. To investigate the state estimation process, the position filtering coefficients are used $\alpha_{pos} = 0,65$ and velocity $\alpha_{vel} = 0,25$, while risk assessment is performed for a specified safe distance $d_s = 1,5\text{m}$ and the potential collision radius $d_c = 0,45\text{m}$, which makes it possible to investigate the performance of the proposed method under different relative motion scenarios of the mobile robot and the dynamic object.

The obtained simulation results are presented in Figures 1–8.

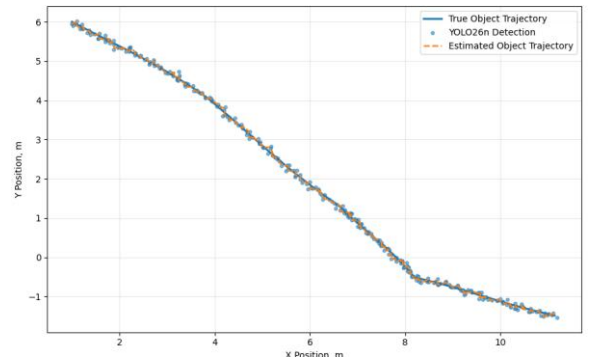


Figure 1 – Dynamic Object Identification and State Estimation

The results presented in Figure 1 show that the estimated trajectory practically coincides with the actual trajectory of the dynamic object, while the YOLO26n detection points exhibit only minor deviations from it. This confirms the ability of the proposed EDGE method to robustly estimate the spatial position of the object even in the presence of the specified coordinate error $\sigma = 0,045\text{m}$ and the probability of missed detection 0,03.

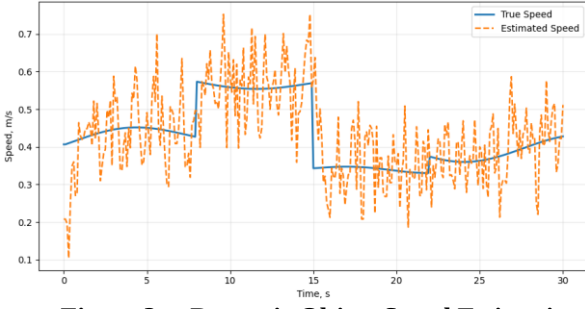


Figure 2. – Dynamic Object Speed Estimation

Figure 2 shows that the actual velocity of the dynamic object varies from approximately 0.35 to 0.57m/s during the simulation, while its estimated value exhibits short-term fluctuations within the approximate range of 0.1–0.75m/s. Nevertheless, the estimated velocity generally follows the changes in the actual velocity, while the quantitative estimation error is RMSE=0.1218m/s, confirming the operability of the dynamic state estimation model..

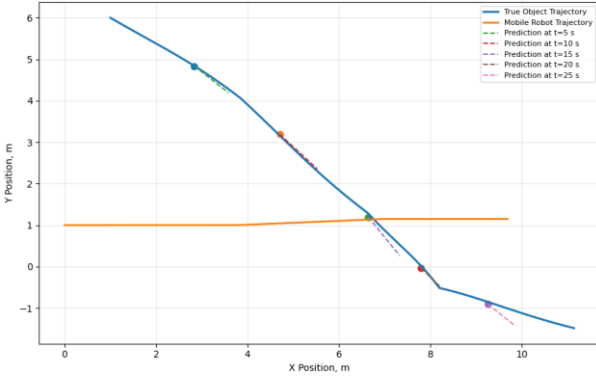


Figure 3. – Short-Term Dynamic Object Trajectory Prediction

The results presented in Figure 3 show that the trajectory segments predicted over a 2.0s horizon generally correspond to the subsequent direction of the actual motion of the dynamic object, including sections where its velocity and direction change. Quantitatively, the prediction accuracy is characterized by RMSE = 0.3193m, MAE = 0.2797m, and a maximum error of 0.9141 m, with the largest deviations occurring, as expected, near the moments when the motion parameters change.

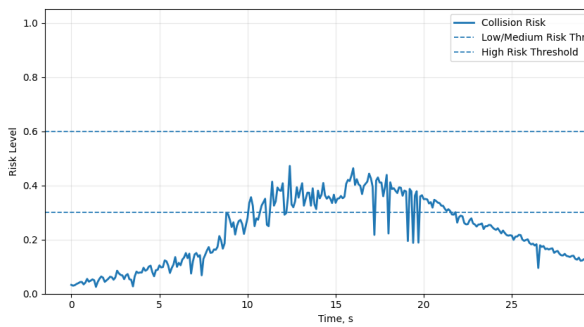


Figure 4. – Dynamic Object Collision Risk Assessment

Figure 4 shows that the calculated collision risk initially increases from approximately 0.03–0.05 to a maximum

value of 0.4719, which is reached approximately within the 14–17s interval, after which it gradually decreases to approximately 0.11 by the end of the simulation. The maximum risk remains below the established high-risk threshold. $R = 0,6m$, and the minimum predicted distance between the mobile robot and the object is 0.8064 m, which exceeds the specified potential collision radius. $d_c = 0,45m$.

1. YOLO26n EDGE identification	
Detection rate	: 96.68 %
Mean confidence	: 0.8912
Detection position RMSE	: 0.0652 m
Detection position MAE	: 0.0578 m

Figure 5. – YOLO26n EDGE identification

The results presented in Figure 5 show that, under the simulated errors and short-term missed detections, YOLO26n achieves a 96.68% successful detection rate with an average confidence value of 0.8912. The position estimation error is characterized by RMSE=0.0652m and MAE=0.0578m, indicating only a small deviation of the EDGE identification results from the specified actual position of the object.

2. Dynamic state estimation	
Position estimation RMSE	: 0.0470 m
Position estimation MAE	: 0.0420 m
Velocity estimation RMSE	: 0.1218 m/s

Figure 6. – Dynamic state estimation

Figure 6 shows that, after filtering the detection results, the position estimation error decreases to RMSE=0.0470m and MAE=0.0420m, meaning that the position RMSE is reduced by approximately 27.9% compared with the direct YOLO26n detection results. At the same time, the velocity estimation RMSE is 0.1218m/s, indicating a higher sensitivity of velocity estimation to coordinate noise and discrete differentiation..

3. Trajectory prediction	
Prediction horizon	: 2.00 s
Prediction RMSE	: 0.3193 m
Prediction MAE	: 0.2797 m
Maximum prediction error	: 0.9141 m

Figure 7. – Trajectory prediction

The results presented in Figure 7 show that, for a prediction horizon of 2.0s, the mean absolute error of the predicted position is 0.2797m, while the root mean square error is 0.3193m, and the maximum short-term deviation reaches 0.9141m. The obtained values indicate that the kinematic model provides effective short-term trajectory prediction; however, the prediction accuracy decreases when the object changes its velocity or direction of motion, which is consistent with the assumptions of the constant-velocity model.

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4. Collision risk
Maximum predicted risk      : 0.4719
Minimum predicted distance  : 0.8064 m

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Figure 8. – Collision risk

Figure 8 shows that the maximum predicted risk level is 0.4719, while the minimum predicted distance between the trajectories of the mobile robot and the dynamic object is 0.8064m. Since this distance exceeds the specified potential collision radius of 0.45m by approximately 0.356m, no direct collision is predicted in the simulated scenario however, the increase in $R(t)$ allows the EDGE system to detect the approach in advance and generate information for adapting the motion of the mobile robot.

IV. CONCLUSION

This paper presents an EDGE method for the identification and trajectory prediction of dynamic objects for a mobile robot based on YOLO26n, which provides local object detection, estimation of their dynamic states, short-term trajectory prediction, and assessment of potential collision risk directly on the onboard EDGE platform. The numerical simulation results confirmed the operability of the proposed method: the successful detection rate was 96.68% with an average confidence of 0.8912, the position estimation RMSE after filtering decreased to 0.0470m, while for a prediction horizon of 2.0s, the trajectory prediction RMSE and MAE were 0.3193m and 0.2797m, respectively. The obtained results confirm the feasibility of using the developed EDGE method for the early detection of hazardous interactions between a mobile robot and dynamic objects and provide a basis for its further practical implementation and experimental validation on a real mobile robotic platform..

REFERENCES

- [1] Ma, J., Xu, L., Li, X., & Liang, Y. (2026). A reproducible workflow for diagnosing YOLO26-to-NCNN deployment inconsistencies on resource-constrained Android devices. *MethodsX*, 104064. <https://doi.org/10.1016/j.mex.2026.104064>
- [2] Nevliudov, I., Yevsieiev, V., Maksymova, S., Pashchenko, O., & Kosenko, V. (2026). Development of a model for synchronizing the operation of collaborative robotic manipulators in HRC scenarios. *INNOVATIVE TECHNOLOGIES AND SCIENTIFIC SOLUTIONS FOR INDUSTRIES*, (2(36)), 214–226. <https://doi.org/10.30837/2522-9818.2026.2.214>
- [3] Nevliudov, I., Yevsieiev, V., Maksymova, S., Gopejenko, V., & Kosenko, V. DEVELOPMENT OF MATHEMATICAL SUPPORT FOR ADAPTIVE CONTROL FOR THE INTELLIGENT GRIPPER OF THE COLLABORATIVE ROBOT MANIPULATOR. *Advanced Information Systems*. 2025 9(3), P. 57–65. DOI: <https://doi.org/10.20998/2522-9052.2025>
- [4] Amer Abu-Jassar, Hassan Al-Sukhni, Yasser Al-Sharo, Svitlana Maksymova, Vladyslav Yevsieiev, Vyacheslav Lyashenko, Building a Route for a Mobile Robot Based on the BRRT and A*(H-BRRT) Algorithms for the Effective Development of Technological Innovations. *International Journal of Engineering Trends and Technology*. 2024. Vol. 72, no. 11, P. 294-306, DOI: <https://doi.org/10.14445/22315381/IJETT-V72I11P129>.
- [5] Wu, Z., Zhang, X., Cui, Y., Yang, Y., & Li, Y. (2026). YOLO-SCC: A Lightweight Object Detection Method for Mine Safety. *Sensors*, 26(15), 4897. <https://doi.org/10.3390/s26154897>
- [6] Nevliudov, I., Omarov, M., Yevsieiev, V., Maksymova, S., & Jabrayilzade, E. MATHEMATICAL MODELING OF TRAJECTORIES CONSTRUCTION, MOVEMENT OF THE GRIPPING DEVICE OF A COLLABORATIVE ROBOT. *Advanced Information Systems*. 2026. 10(1), P. 11–20. DOI: <https://doi.org/10.20998/2522-9052.2026.1.02>.
- [7] Islam, R., Mule, J., Challagundla, D., Rizvi, S., Carson, S., & Saini, R. (2026). LiteEvent-AE: Lightweight Autoencoder for Event-Based Vision on Low-Latency Energy-Constrained Edge Devices. *arXiv preprint arXiv:2608.21764*. <https://doi.org/10.48550/arXiv.2608.21764>
- [8] YEVSIEIEV, V., & GURIN, D. (2026). Development of a model for constructing the optimal trajectory of the gripping device of a collaborative robot-manipulator taking into account the influence of the cargo mass and energy consumption. *Open Information and Computer Integrated Technologies*, 0(107), 224-240. <https://doi.org/10.32620/oikit.2026.107.15>
- [9] Industry 5.0 та колаборативна робототехніка: динамічний опис навколишнього середовища роботів-маніпуляторів з використанням мови Python: монографія / І. Ш. Невлюдов, В. В. Євсєєв, С. С. Максимова. – Харків : Видавництво Іванченка І. С., 2026. – 279 с. <https://doi.org/10.30837/978-617-8332-95-2>
- [10] Model with Neural Network Component for Adaptive Manipulator Control under Variable Load / Amer Abu-Jassar, Mohammad Hamdan, Nowfal Aweisi, Mahmoud Howaidi, V. Yevsieiev, V. Lyashenko // *International Journal of Intelligent Engineering and Systems*. –19(1). – 2026. – P. 855-868. <https://doi.org/10.32403/10.22266/ijies2026.0131.51>
- [11] Attar, H., Abu-Jassar, A., Hafez, M., Al-Sharo, Y. M., Yevsieiev, V., & Lyashenko, V. (2025, December). Model of Spatial Localization and Identification Objects in the Working Area Collaborative Robot. In *2025 Asian Conference on Communication and Networks (ASIANComNet)* (pp. 1-6). IEEE. <https://doi.org/10.1109/ASIANComNet68615.2025.11579708>
- [12] Ababneh, J., Abu-Jassar, A., Hamdan, H., Hafez, M., Yevsieiev, V., & Lyashenko, V. (2025, December). Determining the Trajectory of a Mobile Robot Using Chaotic Dynamical Systems. In *2025 Asian Conference on Communication and Networks (ASIANComNet)* (pp. 1-7). IEEE. <https://doi.org/10.1109/ASIANComNet68615.2025.11579639>