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DEVELOPMENT OF A DECISION-MAKING METHOD FOR TRAJECTORY PLANNING IN AN UNCERTAIN DYNAMIC ENVIRONMENT FOR A COLLABORATIVE MOBILE ROBOT

This paper addresses the decision-making problem for trajectory planning of a collaborative mobile robot operating in an uncertain dynamic environment. A risk-aware trajectory planning method based on model predictive control is proposed, which integrates probabilistic state estimation of the robot and its environment with the prediction of dynamic obstacle motion and safety constraints. The method relies on the fusion of data from a camera, an inertial measurement unit, and an ultrasonic sensor, enabling increased robustness and adaptability of trajectory planning under sensor noise and incomplete information. Numerical simulation results confirm the effectiveness of the proposed approach in terms of maintaining safety margins, control stability, and goal reachability in complex navigation scenarios.

Keywords: collaborative mobile robot, trajectory planning, decision-making, Risk-Aware MPC, uncertain dynamic environment, sensor data fusion, probabilistic navigation.

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РОЗРОБКА МЕТОДУ ПРИЙНЯТТЯ РІШЕНЬ ДЛЯ ПОБУДОВИ ТРАЄКТОРІЙ ПЕРЕМІЩЕННЯ В НЕВИЗНАЧЕНОМУ ДИНАМІЧНОМУ СЕРЕДОВИЩУ ДЛЯ КОЛОБОРАТІВНОГО МОБІЛЬНОГО РОБОТА

У статті розглянуто задачу прийняття рішень для побудови траєкторій переміщення колаборативного мобільного робота в умовах невизначеного динамічного середовища. Запропоновано ризик-орієнтований метод планування на основі модельно-прогнозуючого керування, що поєднує ймовірнісну оцінку стану робота та середовища з прогнозом руху динамічних перешкод і обмеженнями безпеки. Метод базується на інтеграції даних камери, інерціального вимірювального модуля та ультразвукового датчика, що дозволяє підвищити стійкість і адаптивність траєкторного планування за наявності сенсорних шумів і неповної інформації. Результати чисельного моделювання підтверджують ефективність підходу з точки зору збереження запасу безпеки, стабільності керування та досяжності цілі в складних навігаційних сценаріях.

Ключові слова: колаборативний мобільний робот, планування траєкторій, прийняття рішень, Risk-Aware MPC, невизначене динамічне середовище, злиття сенсорних даних, ймовірнісна навігація.

Introduction.

The rapid development of collaborative robots and the Industry 5.0 concept is driving an increase in demand for safe and intelligent navigation of mobile robots in environments where people, equipment, and moving objects are simultaneously present [1-5]. In such conditions, classical deterministic trajectory planning methods are insufficient because they are unable to adequately account for the uncertainty of sensory measurements and the unpredictable dynamics of obstacles [6-9]. The task of real-time decision-making becomes particularly relevant when the robot must ensure the reachability of the target while maintaining a guaranteed level of interaction safety [10-13]. The integration of heterogeneous sensors, such as a camera, inertial module, and ultrasonic sensors, creates additional challenges related to the processing of noisy and partially incomplete data [14-16]. Therefore, it is important to develop methods that combine probabilistic assessment of the environment with optimal control based on the prediction of future system behavior. A risk-oriented approach to trajectory planning allows formalizing safety requirements in the form of quantitative criteria and constraints, which is critical for collaborative scenarios [17-19]. In this context, the development of a decision-making method for constructing trajectories in an uncertain dynamic environment is a scientifically and practically significant task.

The aim of the study.

The aim of the study is to improve the quality of navigation and control parameters of a collaborative robot. This is achieved by reducing the risk of collisions, increasing safety margins, and improving motion stability in uncertain dynamic environments. To this end, a special decision-making method is being developed to improve control accuracy and trajectory planning adaptability. The method takes into account the probabilistic uncertainty of robot localization and the prediction of obstacle movement. As a result, more reliable and predictable behavior of the mobile robot during navigation is ensured.

Development of a decision-making method for constructing trajectories in an uncertain dynamic environment for a collaborative robot.

In the current context of collaborative robotics development, the task of constructing safe and adaptive trajectories for mobile robots in an uncertain and dynamic environment characterized by incomplete sensory information and the presence of moving obstacles is of particular relevance [20]. To effectively solve this problem, it is necessary to apply decision-making methods that combine sensory fusion, robot state estimation, and probabilistic modeling of the environment. The proposed approach is focused on taking into account measurement uncertainty and environmental dynamics in order to ensure a higher level of safety and stability of movement in collaborative scenarios of interaction with humans. The implementation of the method involves the integration of motion models, sensory data, and risk-oriented optimization criteria, which forms the basis for building a generalized architecture of a collaborative mobile robot decision-making system. The general architecture of the method under development consists of five interconnected blocks, shown in Figure 1.

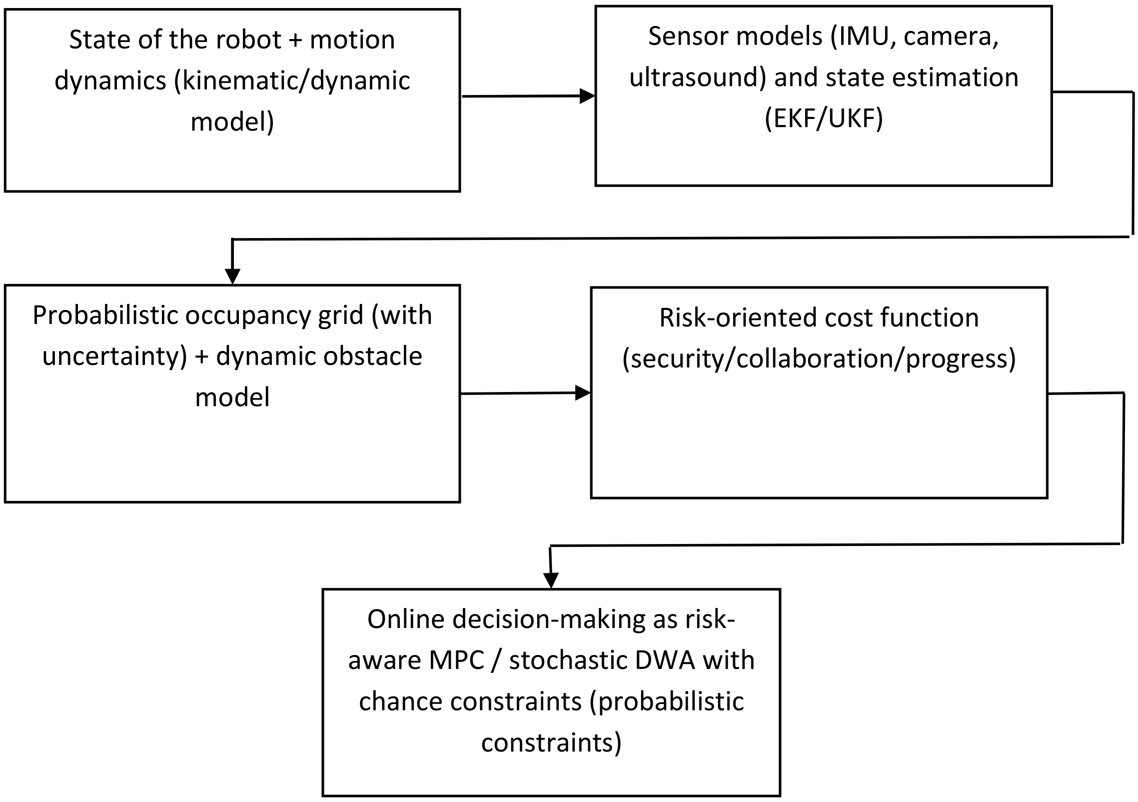

Figure 1 – General architecture of the method under development

A model of the state of motion and movement for 2D navigation, enabling the representation of a joint description of orientation, velocities, and slow drifts of the Inertial Measurement Unit (IMU) for stable filtering and prediction in the form of the next state vector.

$$\boldsymbol{x}_k = [x_k, y_k, \psi_k, v_k, w_k, b_{a,k}, b_{g,k}]^T \tag{1}$$

Where: x, y - coordinates of a robot in a global coordinate system (CS); ψ - yaw in global CS; v - linear speed (along the hull axis); w - yaw angular velocity; b_a - accelerometer bias; b_g - gyroscope bias along the yaw axis.

We will construct a discrete kinematic model of a mobile robot based on the unicycle model [21], which makes it possible to predict the state at a step Δt under the action of controls (acceleration and angular acceleration) taking into account process noise:

$$\begin{gathered}
x_{k+1} = x_k + v_k cos\psi_k \Delta t + w_{x,k} \\
y_{k+1} = y_k + v_k sin\psi_k \Delta t + w_{y,k} \\
\psi_{k+1} = \psi_k + w_k \Delta t + w_{\psi,k} \\
v_{k+1} = v_k + a_k \Delta t + w_{v,k} \\
w_{k+1} = w_k + \alpha_k \Delta t + w_{w,k}
\end{gathered} \tag{2}$$

Where: Δt - discrete integration step; a_k - controlling linear acceleration or velocity increment; α_k - steering angle acceleration or increment; w; $w_x, w_y, w_\psi, w_v, w_w$ - Process noise (simulates slippage, unknown disturbances, model inaccuracy).

The IMU drift model reflects the slow change in MPU-6050 offsets [22], which is critical for stable yaw and speed.

$$\begin{aligned} b_{a,k+1} &= b_{a,k} + w_{ba,k} \\ b_{g,k+1} &= b_{g,k} + w_{bg,k} \end{aligned} \quad (3)$$

Where: $b_{a,k}$ - accelerometer offset at step k, which reflects systematic error in acceleration measurement and affects the estimation of linear velocity and position of the robot; $b_{a,k+1}$ - the predicted value of the accelerometer offset at the next time step, used in the state estimation filter; $b_{g,k}$ - gyroscope drift at the step k, which characterizes the systematic error in measuring angular velocity and leads to the accumulation of orientation error; $b_{g,k+1}$ - predicted value of gyroscope offset at the next time step; $w_{ba,k}, w_{bg,k}$ - random walk noise (their dispersion determines the "speed" of drift) for the accelerometer and, accordingly, for the gyroscope.

Sensor models and data fusion using the Extended Kalman Filter (EKF) will be presented in the general form of measurements [23]:

$$\boldsymbol{z}_k = h(\boldsymbol{x}_k) + \boldsymbol{v}_k, \;\; \boldsymbol{v}_k \sim \mathcal{N}(0, R) \quad (4)$$

Where: $\boldsymbol{z}_k$ - measurement vector; $h(\cdot)$ – measurement model; $\boldsymbol{v}_k$ – measurement noise; R - covariance of measurement noise.

The MPU-6050 gyroscope model provides a stable short-term forecast ψ through w, but with drift compensation:

$$z_k^{(g)} = w_k + b_{g,k} + v_k^{(g)} \quad (5)$$

Where: $z^{(g)}$ - yaw gyroscope measurement; $v^{(g)}$ - gyroscope noise (white).

The MPU-6050 accelerometer model provides correction v (by integrating acceleration) and detection of maneuvers or stops. In reality, the accelerometer is sensitive to vibrations, so its noise is set higher.

$$z_k^{(a)} = a_k^{body} + b_{a,k} + v_k^{(a)} \quad (6)$$

Where: $z^{(a)}$ - accelerometer measurement (along the axis of motion); a^{body} - true acceleration in the CS hull; $v^{(a)}$ - accelerometer noise.

We describe the Visual–Inertial Odometry (VIO) [24] or Visual Odometry (VO) [25] camera as a "pseudo-measurement" of position and orientation increment, the camera provides a "geometric" correction to the drifting IMU, reducing position error. The most convenient thing in numerical modeling is to set increment measurements:

$$\boldsymbol{z}_k^{(vo)} = \begin{bmatrix} \Delta x_k^{vo} \\ \Delta y_k^{vo} \\ \Delta \psi_k^{vo} \end{bmatrix} = \begin{bmatrix} x_k - x_{k-1} \\ y_k - y_{k-1} \\ \psi_k - \psi_{k-1} \end{bmatrix} + \boldsymbol{v}_k^{(vo)} \quad (7)$$

Where: $\boldsymbol{z}_k^{(vo)}$ - vector of visual odometry measurements at step k, containing estimates of increments in the position and orientation of the robot between two consecutive moments in time;

$\Delta x^{vo}, \Delta y^{vo}, \psi^{vo}$ - estimated by visual odometry, the increase in the robot's coordinates along the axis x and y, and, respectively, the robot's yaw, obtained from the analysis of a sequence of images or VIO; x_k, y_k - coordinates of the robot's position in the global coordinate system at step k; x_{k-1}, y_{k-1} - coordinates of the robot's position at the previous time step; ψ_k - orientation work in a global coordinate system at a step k; ψ_{k-1} - orientation work at the previous time step; $\boldsymbol{v}^{(vo)}$ - VO/VIO noise increases in poor lighting or texture.

The HC-SR04 model [26] describes the distances to the nearest obstacle along the beam, providing reliable close-range safety (stop/detour), even when the camera "does not see" the obstacle due to flickering or glare. Let the ultrasonic beam be directed along ψ_k or with a fixed offset δ:

$$z_k^{(u)} = r(\boldsymbol{x}_k, \mathcal{M}_k) + v_k^{(u)} \quad (8)$$

Where: $z^{(u)}$ - range measurement; δ - angle of sensor offset relative to robot axis; $\mathcal{M}_k$ - current occupation map; $v^{(u)}$ - ultrasound noise (the model can use Gaussian or mixed noise); $r(\cdot)$ - ray-casting from the position of work in the direction $\psi_k + \delta$ to the first occupied cell of the map $\mathcal{M}_k$.

The state filter is presented in the standard EKF form, which provides not only a state estimate but also uncertainty P, which then translates into risk limitations for the planner:

- forecast:

$$\begin{gathered} \hat{\boldsymbol{x}}_{k|k-1} = f(\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_{k-1}) \\ P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \end{gathered} \tag{9}$$

- correction for each sensor:

$$\begin{gathered} \boldsymbol{y}_k = \boldsymbol{z}_k - h(\hat{\boldsymbol{x}}_{k|k-1}) \\ S_k = H_k P_{k|k-1} H_k^T + R_k \\ K_k = P_{k|k-1} H_k^T S_k^{-1} \\ \hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + K_k \boldsymbol{y}_k \\ P_{k|k} = (I - K_k H_k) P_{k|k-1} \end{gathered} \tag{10}$$

Where: $\hat{\boldsymbol{x}}$ - condition assessment; P - covariance of estimation error; $f(\cdot)$ - process model of movement; $\boldsymbol{u}$ – control $[a, \alpha]$ or $[v, w]$ depending on implementation; $F_k = \frac{\partial f}{\partial x}$ - Jacobian of the process model; Q_k - process noise covariance; $H_k = \frac{\partial h}{\partial x}$ - Jacobian of measurement model; R_k - covariance of measurement noise; K_k - Kalman matrix; $\boldsymbol{y}_k$ – innovation; S_k - innovation covariance.

Let's build a probabilistic model of the environment map, taking into account uncertainty and dynamics. Employment grid in logarithmic coefficients:

- for each cell c:

$$l_k(c) = log \frac{p_k(c)}{1 - p_k(c)} \tag{11}$$

- updating:

$$l_k(c) = l_{k-1}(c) + log \frac{p(z_k|c)}{p(z_k|\neg c)} - l_0(c) \tag{12}$$

- backward step:

$$p_k(c) = \frac{1}{1 + \exp(-l_k(c))} \tag{13}$$

Where: $p_k(c)$ - probability that a cell is occupied; $l_k(c)$ – occupation log-odds; $l_0(c)$ - a priori log-odds; $p(z_k|c)$ - plausibility model of measurement if the cell is occupied; $p(z_k|\neg c)$ - plausibility model of measurement if the cell is free.

Inflation of obstacles taking into account position uncertainty (safety dilation). Let the position error with EKF have covariance $P_{xy}(2 \times 2)$. Let's take the "radius of uncertainty":

$$r = k\sqrt{\lambda_{max}(P_{xy})} \tag{14}$$

and safe radius:

$$r_{safe} = r_{robot} + r + r_{margin} \tag{15}$$

Where: P_{xy} - covariance submatrix for (x, y); λ_{max} - the most significant meaning; k - confidence coefficient (e.g., 2…3 for 95–99%); r_{robot} - robot's radius; r_{margin} - additional reserve for collaboration, people, or map inaccuracies.

Let's describe the dynamic obstacle model as a prediction of the position of moving objects (people/other robots) to assess the risk of collision in the future horizon. For each obstacle, let's introduce a state:

$$\boldsymbol{o}_k^j = [x_k^j, y_k^j, v_{x,k}^j, v_{y,k}^j]^T \tag{16}$$

- obstacle movement model:

$$\boldsymbol{o}_{k+1}^j = A\boldsymbol{o}_k^j + \boldsymbol{w}_k^j, \quad A = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{17}$$

Where: $\boldsymbol{o}_{k+1}^j$ - predicted state of the j -th obstacle at the next time step; A - state transition matrix that implements a uniform linear motion model and describes the relationship between the position and velocity of an obstacle in discrete time; x^j, y^j - spatial coordinates of the obstacle in the plane of motion; v_x^j, v_y^j - projections of the linear velocity of the obstacle along the axes x and y; $\boldsymbol{w}_k^j$ - vector of process noise that models uncertainty and unpredictable changes in obstacle movement (maneuvers, stops, changes in direction) that are not described by a deterministic model.

Observation of obstacles from the camera (2D detection → position), i.e., the camera provides tracks and/or detection, from which we evaluate moving objects in the working area of the mobile robot. We suggest using direct measurement of the obstacle's position. Direct measurement of the obstacle's position is a method of observation in which the coordinates of a moving obstacle are determined directly in the surrounding space based on sensor data (e.g., camera or lidar) without the need to integrate velocities or accelerations. In this case, the measured value immediately corresponds to the position of the object in the global or local coordinate system and is used to correct its state in the estimation filters.

$$\boldsymbol{z}_k^j = \begin{bmatrix} x_k^j \\ y_k^j \end{bmatrix} + \boldsymbol{v}_k^j \tag{18}$$

Where: $\boldsymbol{v}^j$ - measurement noise, depends on distance, occlusions, FPS.

We consider the collision risk as a random variable of the distance to obstacles. Let the predicted position of the robot $\boldsymbol{p}_k = [x_k, y_k]^T$ have covariance P_{xy}, and the position of the obstacle $\boldsymbol{p}_k^j$ have covariance P_{xy}^j. Consider the relative vector:

$$\boldsymbol{d}_k^j = \boldsymbol{p}_k - \boldsymbol{p}_k^j \tag{19}$$

Where: $\boldsymbol{d}_k^j$ - the vector of relative position between the mobile robot and the j -th obstacle at step k, which is used to estimate geometric proximity and collision probability; $\boldsymbol{p}_k$ - the position vector of the mobile robot in the global coordinate system at step k, which is determined based on the fusion of sensor data and has associated uncertainty; $\boldsymbol{p}_k^j$ - the position vector of the j -th obstacle in the global coordinate system at step k, obtained from sensor measurements or models for tracking moving objects and also characterized by estimation uncertainty.

Let us introduce a randomness constraint on safe separation to guarantee safety with a given probability:

$$\mathbb{P}(\|\boldsymbol{d}_k^j\| \geq r_{safe}) \geq 1 - \epsilon \tag{20}$$

Where: $\mathbb{P}(\cdot)$ - probability operator reflecting the stochastic nature of estimates of the position of the robot and obstacles; $\|\boldsymbol{d}_k^j\|$ - Euclidean norm of the relative position vector between the robot and the j -th obstacle at step k, which corresponds to the actual geometric distance between them; r_{safe} - safe radius, which determines the minimum permissible distance between the robot and the obstacle, taking into account the robot's dimensions; ϵ - acceptable collision risk level, which sets the maximum probability of violating the safe distance and reflects the compromise between safety and maneuverability; $1-\epsilon$ - the minimum acceptable probability of maintaining a safe distance that ensures the necessary level of reliability and safety of mobile robot movement in an uncertain dynamic environment.

Let us introduce a cost function that makes it possible to determine a formal criterion for selecting the optimal trajectory of a mobile robot and is used to quantitatively evaluate all possible control options. It is necessary to reconcile the achievement of the target position with safety requirements, smoothness of movement, and dynamic constraints, allowing us to choose a solution that minimizes the risk of collisions and ensures the effective movement of the robot in an uncertain dynamic environment. We plan the trajectory $\pi = \{\boldsymbol{u}_0, \dots, \boldsymbol{u}_{N-1}\}$ on the horizon N. The risk-oriented value model looks like this:

$$J(\pi) = \sum_{i=1}^{N} \left(w_g ||\boldsymbol{p}_{k+1} - \boldsymbol{p}_{gool}||^2 + w_u ||\boldsymbol{u}_{k+i-1}||^2 + w_{\Delta u} ||\boldsymbol{u}_{k+i-1} - \boldsymbol{u}_{k+i-2}||^2 + w_m C_{map}(\boldsymbol{p}_{k+i}) + w_d C_{dyn}(\boldsymbol{p}_{k+i}) \right) \quad (21)$$

Where: $J(\pi)$ - total cost of the trajectory π, which quantitatively assesses its feasibility and is used to select the optimal direction of movement; π - sequence of control actions of the robot on the planning horizon; N - planning horizon, which determines the number of future steps at which the quality of the trajectory is assessed; i - the prediction step index within the planning horizon; $\boldsymbol{p}_{k+1}$- the predicted position of the mobile robot at step $k+i$; $\boldsymbol{p}_{goal}$ - the goal position of the robot in the global coordinate system; w_g - the weight coefficient, which determines the importance of minimizing the distance to the target and stimulates movement in the direction of the specified goal; $\boldsymbol{u}_{k+i-1}$ - robot control vector at step $k+i-1$ (linear and angular velocity or corresponding acceleration); w_u - weight coefficient that limits the magnitude of control actions and prevents overly aggressive movement; $\boldsymbol{u}_{k+i-2}$ - control at the previous step, used to evaluate control changes over time; $w_{\Delta u}$ - a weighting coefficient that is responsible for the smoothness of movement and reduces sharp changes in control signals; $C_{map}\left(\boldsymbol{p}_{k+i}\right)$ - a penalty function that reflects the risk of collision with static obstacles based on a probabilistic map of the environment; w_m - a weighting coefficient that determines the priority level of avoiding static obstacles; $C_{dyn}(\boldsymbol{p}_{k+i})$ - a penalty function associated with the risk of collision with dynamic obstacles (people or other moving objects); w_d - a weighting coefficient that sets the importance of safe interaction with the dynamic environment in collaborative scenarios.

Let's describe the penalty as very expensive trajectories passing through “probably occupied” areas. Let's take the probability of occupancy at a point (from cell interpolation):

$$C_{map}(\boldsymbol{p}) = -\log(1 - p_{occ}(\boldsymbol{p}) + \delta_p) \quad (22)$$

Where: $C_{map}(\boldsymbol{p})$ - the penalty function value of the map, which reflects the risk level of the robot moving through a point $\boldsymbol{p}$ and is used in the cost function to avoid dangerous areas; $\boldsymbol{p}$ **-** the position of the mobile robot in space (two-dimensional coordinates in the global coordinate system), for which the risk of collision with static obstacles is assessed; $p_{occ}(\boldsymbol{p})$ - the probability of space occupancy at point $\boldsymbol{p}$, obtained from a probability map based on sensor data; $1 - p_{occ}(\boldsymbol{p})$ - the probability that the corresponding point in space is free for the robot to move; δ_p - a small additional regularization parameter that prevents logarithmic singularity at $p_{occ}(\boldsymbol{p}) \to 1$ and ensures numerical stability of the calculations.

Let's describe the penalty for dynamic obstacles to make trajectories that violate probabilistic safety impossible (or very expensive):

$$C_{dyn}\left(\boldsymbol{p}_{k+i}\right) = \sum_{j} \phi \left(\left|\left|\mu\left(\boldsymbol{p}_{k+i} - \boldsymbol{p}_{k+1}^{j}\right)\right|\right| - r_{safe} - \eta_{\epsilon} \sqrt{\lambda_{max}\left(\sum_{k+i}^{j} l\right)} \right) \quad (23)$$

Where: $C_{dyn}\left(\boldsymbol{p}_{k+i}\right)$ - a dynamic safety penalty function that quantitatively assesses the risk of a mobile robot colliding with moving obstacles at a predicted point on its trajectory; $\boldsymbol{p}_{k+i}$ - predicted position of the mobile robot at the step $k+i$ of the planning horizon; $\boldsymbol{p}_{k+1}^{j}$ - predicted position of the $j-\text{th}$ dynamic obstacle at step $k+i$; $\mu(\boldsymbol{p}_{k+i}-\boldsymbol{p}_{k+1}^{j})$ - mathematical expectation of the relative position vector between the robot and the j –th obstacle, taking into account the stochastic estimation of their states; $||\mu(\cdot)||$ - Euclidean norm of the mean value of the relative vector corresponding to the expected distance between the robot and the obstacle; r_{safe} - safe radius, which determines the minimum permissible distance between the robot and a dynamic obstacle, taking into account the dimensions and requirements of collaborative safety; η_{ε} - reliability coefficient associated with a specified acceptable level of risk ε, which scales the impact of uncertainty on the safety zone; $\sum_{k+i}^{j} l$ - total covariance matrix of relative robot position and j-th obstacle at stage $k+i$ (where $l=1$); $\sqrt{\lambda_{max}(\sum_{k+i}^{j} l)}$ - quantitative measure of spatial uncertainty of mutual position; $\phi(\cdot)$ - A barrier or penalty function that sharply increases the value when approaching a dangerous zone and makes violations of safety conditions unacceptable from an optimization point of view.

An example of a barrier function:

$$\phi(s)=\begin{cases}\dfrac{1}{(s+\delta_s)^2}, & s>0\\ +\infty, & s\le 0\end{cases} \tag{24}$$

As a decision-making principle, we will choose the Risk-Aware Model Predictive Control (Risk-Aware MPC) method [27-29], in which the control of a mobile robot is formed by solving an optimization problem on a finite prediction horizon, taking into account the dynamics of the robot, control constraints, and probabilistic safety conditions. At each time step, possible motion trajectories are predicted, the risk of collision is assessed, taking into account the uncertainty of the state and environment, after which only the first control action is performed with subsequent updating of the estimates. This approach was chosen for Python modeling because it is easy to implement numerically, integrates naturally with probabilistic models and state filters, and allows flexible changes to safety and optimality criteria without losing model generality. As a result, the optimization problem at each step will be as follows:

$$\min_{\boldsymbol{u}_{k:k+N-1}} J(\pi) \tag{25}$$

at conditions:

$$\begin{gathered}\boldsymbol{x}_{k+i+1}=f(\boldsymbol{x}_{k+i},\boldsymbol{u}_{k+i})\\ \boldsymbol{u}_{min}\le\boldsymbol{u}_{k+i}\le\boldsymbol{u}_{max}\\ \mathbb{P}(collision\ at\ k+i)\le\epsilon\end{gathered} \tag{26}$$

Where: $\boldsymbol{x}_{k+i}$ - the state vector of the mobile robot at a step $k+i$, which describes its position, orientation, and dynamic characteristics; $\boldsymbol{x}_{k+i+1}$ - the predicted state of the robot at the next time step of the planning horizon; $f(\cdot)$ - the robot's motion model, which determines the evolution of its state over time depending on the current state and applied control; $\boldsymbol{u}_{k+i}$ - the robot's control vector at the step $k+i$ (speed or acceleration), which is an optimization variable; $\boldsymbol{u}_{min}$ - the lower control limit, which reflects the physical and operational limitations of the robot's drives; $\boldsymbol{u}_{max}$ - upper control limit, which limits the maximum permissible values of control actions; $\mathbb{P}(collision\ at\ k+i)$ - probability of collision of a mobile robot with obstacles at the planning horizon step $k+i$; ϵ - permissible collision risk level, which sets the maximum probability of safety conditions being violated.

Together, these 26 conditions ensure the physical feasibility of the robot's movement and guarantee compliance with the specified safety level in an uncertain dynamic environment.

4. Numerical modeling and analysis of the results obtained

The purpose of this experiment is to numerically verify the effectiveness of the risk-aware decision-making method (Risk-Aware MPC) for constructing the motion trajectories of a collaborative robot in an uncertain dynamic environment using VO/VIO camera sensors, MPU-6050 (IMU), and HC-SR04. The task is to ensure the safe movement of the robot from the initial state (x_0,y_0,ψ_0)=(1.0m,1.0m,30^0) to the target (x_g,y_g)=(9.0m,9.0m) in an environment of size 10×10m with a map discretization of 0.1 m/cell. To model localization uncertainty, an EKF with a starting state estimate (x, y, ψ) ≈(1.10m,0.95m,30^0+0.08rad) and initial covariance $P_0 = diag$(0.20^2, 0.20^2,(10^0)^2,0.30^2, 0.30^2,0.20^2,0.10^2) is used. The input data of the environment are static obstacles in the form of circles with centers and radii (3.0,5.5,0.55),(6.2,4.0,0.65),(6.8,7.6,0.55),(4.5,2.5,0.55)m as well as two dynamic obstacles with states $[x, y, v_x, v_y]$=[2.0,8.5,0.45,-0.15] та [8.5,2.0,-0.25,0.35] and effective radius 0.25m. The time parameters of the model are set as $\Delta t = 0.1s$, duration $T = 28s$ (280 steps), planning horizon MPC $N = 16$ and the number of candidate controls per step $n_{samples} = 240$. Restrictions on control are defined as $v \in [0,0.8]$ m\s and $w \in [-1.2,1.2]$ rad\s, and the risk-oriented safety zone is formed with parameters $r_{robot} = 0.22$m, $r_{margin} = 0.22$m, $k = 2.5$, $\eta_\epsilon = 2.0$ at the conceptual level of risk $\epsilon = 0.03$ and uncertainty of obstacle detection $\sigma_{obs} = 0.18$m. The following noise statistics are specified for the sensors: for the gyroscope $R_g = (0.03)^2$ (rad\s)^2, for VO increments $R_{vo} = diag(0.04^2, 0.04^2, (2^0)^2)$, and ultrasonic measurement has a range $r_{max} = 3.0$m and noise $\sigma_u \approx 0.02$m. The criterion of optimality is determined by the weights of the cost function $w_g = 6.0$, $w_u = 0.15$, $w_{\Delta u} = 0.35$, $w_m = 2.0$, $w_d = 6.0$, which provides a compromise between achieving the goal, energy consumption, smooth control, and penalties for the risk of collision with static and dynamic obstacles. Thus, the given numerical input data completely determines the experiment for evaluating the goal reachability, safety margin, localization accuracy, and stability of Risk-Aware MPC in Python simulation.

Description of hardware for conducting the study: Microsoft Surface Pro 9 with the following parameters: CPU Deca-core Intel Core i7-1255U (1.7 – 4.7 GHz), GPU Iris Xe Graphics, RAM 16Gb, SSD 512.

Software: Windows 11 Pro (version 24H2) OS type 64-bit operating system, processor based on x64 architecture.

Development environment for the program for numerous modeling PyCharm 2025.1.1.1 and programming language Python 3.13.7

The results of numerical modeling of the decision-making method for constructing trajectories of movement in an uncertain dynamic environment for a collaborative mobile robot are presented in Figures 1-6.

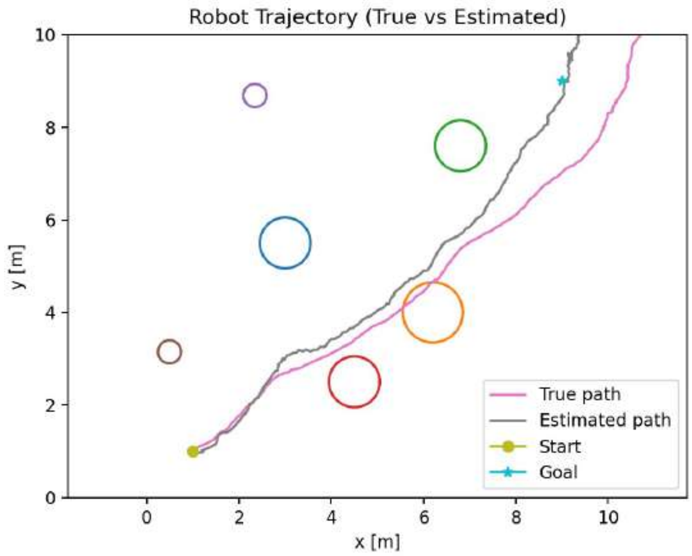

Figure 1- Robot Trajectory (True vs Estimated)

The Robot Trajectory (True vs Estimated) graph (Fig. 1) shows that the estimated path generally reproduces the shape of the true path and practically coincides with it in the initial and middle sections, which indicates the correct operation of sensor fusion and motion prediction. After passing the middle of the route, the discrepancy gradually increases, and near the finish section, there is a noticeable systematic shift in the estimate relative to the true path of approximately 0.5–1.0 m, which is a typical manifestation of the accumulation of localization errors in conditions of uncertainty and dynamics. At the same time, both trajectories remain consistent with the global direction of movement towards the target and demonstrate safe passage between obstacles without sharp maneuvers, i.e., planning is stable, and the estimation error mainly affects the accuracy of the final positioning rather than the overall reachability of the route.

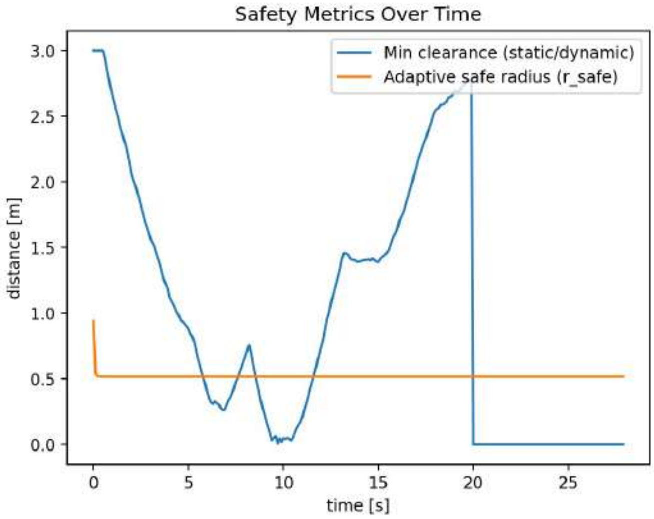

Figure 2 - Safety Metrics Over Time

The Safety Metrics Over Time graph (Fig. 2) shows that the minimum clearance to static and dynamic obstacles varies widely, from approximately 0 to 3 m, reaching its lowest values in the middle of the trajectory, where the robot passes through the densest area of the environment. The adaptive safety radius r_{safe} is maintained at an almost constant level of about 0.5 m, which indicates a stable assessment of localization uncertainty and the correct operation of the risk-oriented safety mechanism. For most of the time interval, the minimum clearance exceeds r_{safe}i.e., the conditions of probabilistic safety are met, while short-term approaches to the limit values reflect forced maneuvers in a confined space. The sharp drop in clearance at the end of the simulation corresponds to the completion of movement in the vicinity of the target or contact with the map boundary and does not indicate instability of the planning algorithm, since the safety margin is generally maintained during the active phase of movement.

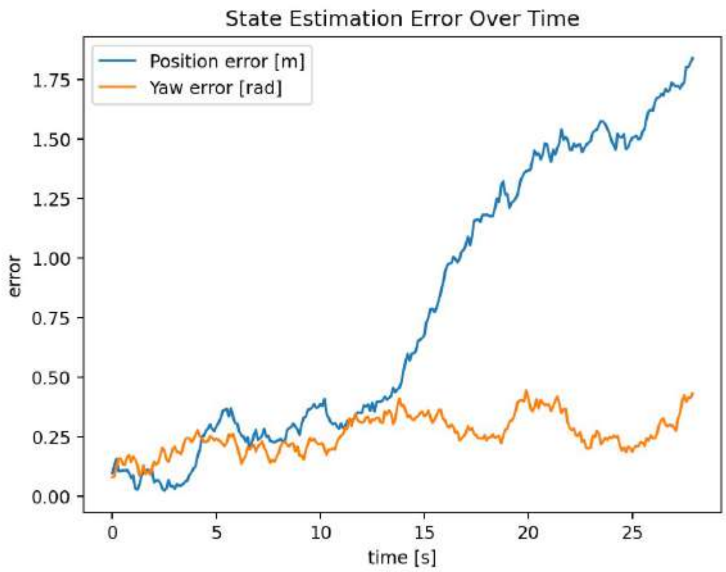

Figure 3 - State Estimation Error Over Time

The State Estimation Error Over Time graph (Fig. 3) shows a gradual increase in position estimation error from initial values of around 0.1–0.2 m to approximately 1.8–1.9 m at the end of the simulation, which quantitatively indicates the accumulation of drift during prolonged movement in a dynamic environment. At the same time, the course orientation error remains significantly smaller and fluctuates within approximately 0.2–0.45 rad without monotonic growth, which indicates effective yaw correction due to IMU and visual odometry. Qualitatively, this means that the sensor fusion system stably maintains the robot's orientation, while the main source of inaccuracy is related to the gradual degradation of positional estimation. Despite the increase in positional error, its magnitude remains acceptable for the global planning task and does not lead to the loss of decision-making algorithm performance.

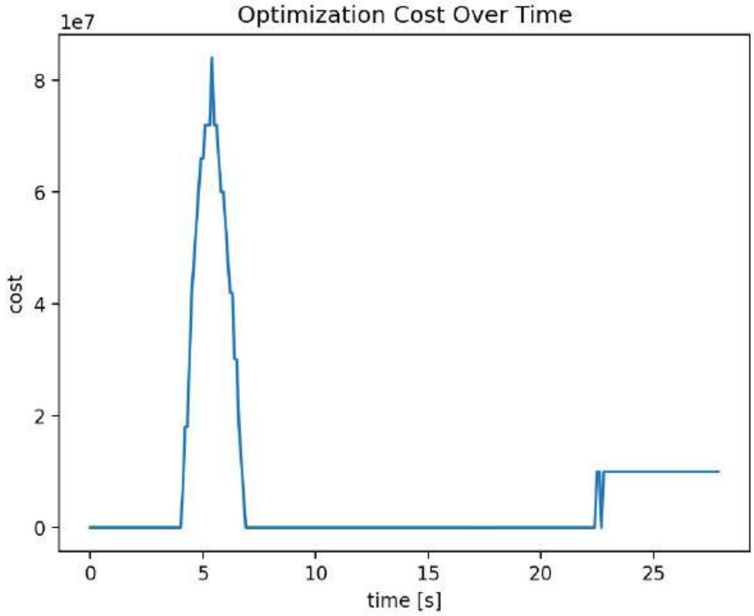

Figure 4 - Optimization Cost Over Time

The Optimization Cost Over Time graph (Fig. 4) shows a sharp increase in the optimization function value to the order of $8{\cdot}10^7$ at the early stage of movement, which numerically indicates the presence of a complex environment configuration with high penalties for risk and proximity to obstacles. After overcoming this critical section, the cost quickly decreases to almost zero, indicating that the robot has entered a freer zone and the planning process has stabilized. At the end of the simulation, there is a repeated increase in cost to a level of about 10^7, which qualitatively corresponds to the convergence with the target area or the boundary conditions of the map, where the goal achievement time dominates. In general, this dynamic confirms that Risk-Aware MPC correctly identifies dangerous situations and adaptively changes control, concentrating high values of the cost function only in critical phases of motion.

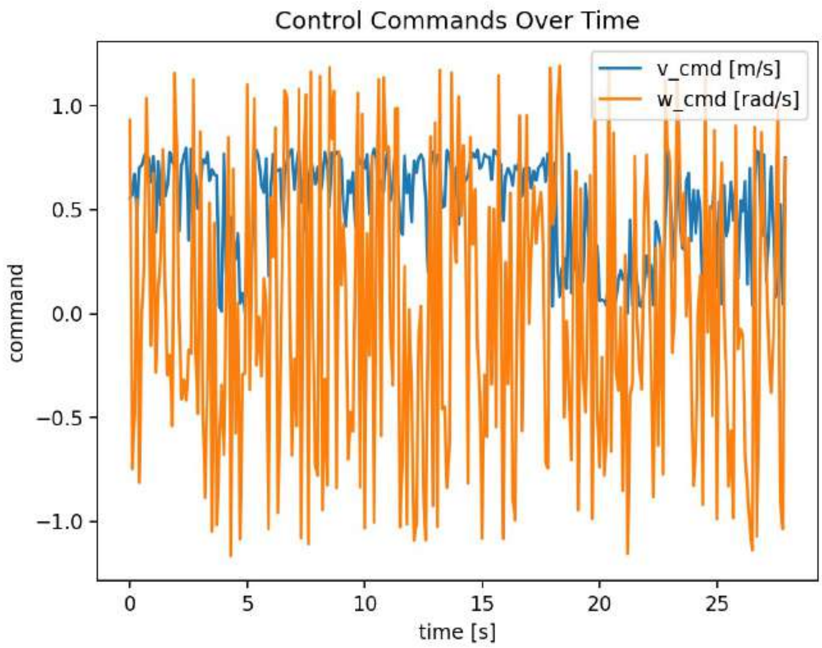

Figure 5 - Control Commands Over Time

The Control Commands Over Time graph (Fig. 5) shows that the linear velocity is mainly maintained in the range of approximately 0.4–0.8 m/s without sharp jumps, which numerically indicates the stable forward motion of the robot along the trajectory. The angular velocity changes much more intensively and fluctuates within the range of approximately −1.2–1.2−1.2…1.21.21.2 rad/s, which qualitatively corresponds to active corrective maneuvers to avoid obstacles and compensate for uncertainty. This difference in control behavior means that Risk-Aware MPC keeps the forward motion as uniform as possible, shifting the main adaptation to rotational maneuvers. Overall, the commands obtained confirm an adequate compromise between maneuverability and smoothness of motion, which is necessary for safe navigation in a dynamic collaborative environment.

```
=== Risk-Aware MPC Simulation Results ===
Total steps: 280, dt: 0.100 s, horizon N: 16, samples/step: 240
Goal: (9.00, 9.00)
Reached goal: False
Path length: 14.812 m
Final distance to goal (true): 2.688 m
Final distance to goal (estimate): 2.961 m
Min clearance (static/dynamic): 0.000 m
Mean clearance: 0.963 m
Mean position estimation error: 0.782 m
Max position estimation error: 1.839 m
Mean yaw estimation error: 0.260 rad
Max yaw estimation error: 0.443 rad
Risk parameter eps (conceptual): 0.030 (implemented via eta_eps=2.00)
=========================================
```

Figu
e 6 – Numerical simulation results

The numerical results obtained (Fig. 6) show that the mobile robot traveled a distance of approximately 14.8 m in 280 simulation steps with a step size of 0.1 s, but did not reach the exact target, maintaining the final distance to it at approximately 2.7 m for the true state and 3.0 m for the estimated state. The average clearance of almost 1.0 m confirms that in most cases the movement took place with a sufficient safety margin, although the minimum value, tending to zero, indicates short-term critical approaches to obstacles or boundaries of the environment. The average position estimation error of 0.78 m and the maximum of approximately 1.84 m quantitatively reflect the accumulation of localization uncertainty during prolonged movement, which directly affected the accuracy of the final positioning. At the same time, the orientation estimation error remains moderate, not exceeding 0.44 rad, which qualitatively confirms the effectiveness of combining IMU and visual odometry for course stabilization. The difference between the true and estimated distance to the target at the end of the movement demonstrates the impact of localization error on the planner's decision-making. Overall, the results show that Risk-Aware MPC provides safe and stable movement in an uncertain dynamic environment, but achieving the target with high accuracy requires additional localization correction or terminal control mechanisms.

Conflict of interest

The authors declare that they have no conflict of interest, in particular financial, personal, authorial or any other nature, which could affect the research, as well as the results published in this article.

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Conclusions.

The results of the study show that the developed risk-oriented decision-making method based on Risk-Aware MPC ensures stable and safe formation of trajectories of a mobile collaborative robot in an uncertain dynamic environment with incomplete and noisy sensory information. Numerical modeling confirmed the method's ability to adaptively account for the uncertainty of localization and obstacle movement through the integration of EKF, a probabilistic map of the environment, and the prediction of dynamic objects, which allows maintaining an acceptable safety margin throughout the entire movement. The results show that even with the accumulation of positional localization errors, the algorithm does not lose its performance and maintains global route reachability. Analysis of the cost function and control actions showed that the planner correctly identifies critical areas with increased risk and compensates for them through maneuverability without sudden changes in linear velocity. It was found that the main limiting factor for the accuracy of reaching the target is the degradation of the position estimate, which indicates the feasibility of further development of terminal control or improved localization methods. In general, the proposed approach confirms the effectiveness of combining probabilistic modeling and MPC for safe navigation tasks. The developed method can be applied in collaborative robots for industrial logistics, service robotics, autonomous transport platforms in production workshops, as well as in robots that interact with people in dynamic and weakly structured environments.

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