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MATHEMATICAL MODELING OF A DECENTRALIZED ARCHITECTURE FOR CONTROLLING COLLABORATIVE WORK USING SENSOR NETWORKS

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ABSTRACT

The article considers the problem of building a decentralized architecture for controlling collaborative robots based on sensor networks, which is a relevant task for intelligent production systems of Industry 5.0. Mathematical models and expressions are proposed that describe information exchange between agents, conditions for safe interaction and coordinated movement. A numerical modeling method based on the use of barrier functions, consensus algorithms and local sensor information is developed. The computer modeling confirmed that even in the presence of measurement noise, the system ensures coordinated movement of robots without collisions and with observance of a safe distance. The results obtained demonstrate the effectiveness of the decentralized approach and open up prospects for its use in complex collaborative scenarios of industrial automation.

Keywords: Decentralized Control, Collaborative Robots, Sensor Networks, Mathematical Modeling, Barrier Functions, Consensus, Industry 5.0, Numerical Modeling, Multi-Agent Systems.

INTRODUCTION

In the current conditions of Industry 5.0 development, special attention is paid to collaborative robots that are able to effectively interact not only with humans, but also

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with each other in a shared working environment [1]-[18]. One of the key challenges is the development of decentralized control systems that ensure the autonomy, flexibility, and reliability of robotic teams [19]-[24].Therefore, various methods and approaches can be used here [25]-[45].

Traditional centralized approaches are limited by high requirements for computing resources and are vulnerable to the failure of the central node, which reduces the stability of the system in a dynamic environment. Therefore, the use of sensor networks as a basis for data exchange between agents is relevant, allowing robots to form collective decisions based on local information.

The use of mathematical modeling in this context provides the opportunity to formalize the dynamics of movement, interaction, and safety constraints, which is critically important for real-time robot coordination. Decentralized architectures allow robotic systems to scale without loss of efficiency and provide resilience to random network failures. Sensor networks open up the possibility of data processing in a distributed manner, increasing the speed of response to environmental changes. In addition, the use of mathematical models allows you to assess the impact of communication limitations, sensor noise and network structure variability on the quality of control.

Thus, research in the direction of mathematical modeling of decentralized control architecture using sensor networks has high scientific and applied significance, as it contributes to the creation of intelligent robotic systems of a new generation.

RELATED WORKS

In the work of Chen Wen-Tse and Minh Nguyen and the others, a decentralized MARL approach is proposed for coordinating a team of quadrupedal robots when towing a load on cables; the authors train policies according to the centralized-training decentralized-execution scheme and show the scalability and robustness of the approach in realistic experiments, which allows for autonomous decision-making based on local observations [46]. However, for our research on mathematical modeling of decentralized architecture with sensor networks, the results of the formalization of CTDE and the policy learning methodology are useful, which can be used to build a distributed decision-making model; it is difficult to directly apply the MARL implementation to problems with

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CBF/consensus, since MARL approaches provide empirical policies without explicit analytical guarantees of stability or constraint enforcement, which is critical for a formal mathematical model.

In the paper by Pey Javier and Bhagya Samarakoon and the others, a Dec-POMDP/MARL framework is developed for area coverage and moving obstacle avoidance by many reconfigurable robots, with an emphasis on partially observed space and local cooperation, which allows formalizing observation uncertainty and distributed planning [47]. For our mathematical modeling, this provides a useful theoretical basis for introducing belief states and distributed filters (DKF/DEKF) into the sensor network model; however, directly implementing complex Dec-POMDP calculations into numerical simulations of decentralized CBF/MPC systems can be computationally heavy and do not provide strong security guarantees, so they should be used as a conceptual layer (belief models) or for comparative experiments.

The review by Duorinaah F. X. and Rajendran M. and the others, systematizes approaches to human-multi-robot collaboration in interiors, emphasizing safety methods, task planning, and context-sensitive coordination, which are important for practical deployments in construction and industry [48]. From the perspective of our model, useful conclusions concern safety requirements, human interaction models, and risk assessment methods – these results can be incorporated into CBF constraints and task prioritization models; however, the review does not provide specific formalized decentralized equations, so its application is auxiliary to the formulation of practical scenarios.

In the work of Lopes W. A. C. and Rusteiko A. C. and the others, the integration of Digital Twin, IoT and LoRa for SCARA robots in decentralized automation with wireless sensor networks is proposed, demonstrating how WSN and DT improve the monitoring and scalability of the system [49]. For our study, the practical value lies in the specification of network properties (latencies, throughput, delivery probability) and in the ways of integrating WSN with digital twins – these elements can be directly reflected in the model A(t),τ_ij,p_i j but the hardware-oriented LoRa protocols and DT-engineering details will be redundant in the abstract mathematical model and require simplifications.

In the article Gutierrez G. M. and Rincon J. A. and the others, a federated learning approach for collaborative robotics based on ROS2 is presented, which allows distributed model training without data centralization and reduces network load, which is useful for supporting adaptive policies in robots [50]. For mathematical modeling, this makes it possible to introduce a level of parameter adaptation (online tuning of controller coefficients or weights in DKF) without centralized data collection; however, FL procedures usually require additional synchronization mechanisms and do not guarantee the fulfillment of strict safety constraints in real time, so their application to CBF/MPC should be designed with caution.

The review by Trigka M. and Dritsas E. and the others, on Wireless Sensor Networks provides fundamental insights into topologies, energy management, transmission protocols, and reliability strategies that are basic for modeling the network aspects of decentralized control systems [51]. In the context of our work, these results can be used to select realistic models A(t),τ_ij,p_i j and to analyze the robustness of algorithms to losses/delays; however, deep network optimizations and energy models go beyond the scope of classical control mechanics and must be reduced to parametric descriptions in a mathematical model.

In the study of Habib M. K. and Chukwuemeka C. I. and the others, IoT-oriented hybrid autonomous network robots and ANR architectures that combine MRS and WSN for data coverage and routing are described; this provides practical recipes for building hybrid systems with cloud services [52]. For our model, the ideas about the hybrid interaction of local computing and cloud analytics are valuable (useful for offline analysis and training), but direct dependence on cloud interfaces or specific platforms is not necessary in a formalized mathematical model of decentralized control.

In the work of Oh Jaehong and the others, the concept of "cognitive collaborative robots" with a semantic level of integration, explained control and context-oriented planning is highlighted; this is important for increasing the clarity of decisions and the safety of interaction with a person [53]. For our mathematical modeling, we can borrow ideas about semantic representations of the environment and extending the state-vector to semantic features, which will improve decision-making models; however, the integration of a full-fledged cognitive level will significantly complicate the mathematical formulation and will require additional modules (e.g., POMDP/semantic mapping), so its application to the basic decentralized CBF/MPC architecture should be modular.

A review by Puttero S. and Verna E. and the others, on the use of collaborative robots in quality control, systematizes current cases and shows that cobots are useful for

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inspections and integration into production lines, but are often limited by integration costs and regulatory aspects [54]. From our modeling perspective, the results are useful for generating practical testing scenarios (which tasks and constraints should be set in the simulation), but do not suggest new formal algorithms for decentralized control; therefore, they should be used as a source of requirements and evaluation criteria.

In general, the analyzed publications confirm the high relevance and interdisciplinary nature of research in the field of decentralized architectures for controlling collaborative robots using sensor networks: on the one hand, modern works offer MARL/Dec-POMDP and federated learning as tools for distributed adaptation and planning, and on the other hand, works on WSN, DT and industrial applications provide applied network model parameters and security requirements that need to be taken into account. This emphasizes the need for further mathematical formalization (CBF, DKF, distributed optimization) and validation in simulation and experiments to combine the adaptability of modern ML approaches with analytical guarantees of security and scalability.

DEVELOPMENT OF MATHEMATICAL MODELS OF A DECENTRALIZED ARCHITECTURE FOR CONTROLLING COLLABORATIVE ROBOTS USING SENSOR NETWORKS

Modern trends in the development of intelligent production systems require collaborative robots to have the ability to make independent decisions and effectively interact in a dynamic environment. One of the key areas is a decentralized control architecture based on sensor networks and ensuring the stability, scalability and adaptability of robotic systems. The use of sensor networks allows for the exchange of local information between agents, which forms the basis for collective coordination. In this context, the development of mathematical models capable of describing the principles of functioning and interaction of such an architecture is of particular importance.

Dynamic model of an agent (robot) - describes the motor/kinematic/dynamic state of each robot (position, speed, angles, forces). It is used for simulation and for the design of local controllers. It can be represented as a differential model of a mobile robot (unicycle) in the plane:

$$\dot{x}_i(t) = v_i(t)cos\theta_i(t), \tag{1}$$

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$$\dot{y}_i(t) = v_i(t) sin\theta_i(t),$$
$$\dot{\theta}_i(t) = w_i(t),$$

or in vector form:

$$\dot{s}_i = f(s_i, u_i) + w_i, \text{де } s_i = [x_i, y_i, \theta_i]^\intercal, u_i = [u_i, w_i]^\intercal, \quad (2)$$

x_i, y_i – the i-th robot coordinates; θ_i – orientation; v_i – linear speed (command); w_i – angular velocity (command); $w_i(t)$ – model/process noise (vector), e.g. Gaussian with covariance matrix Q_i.

Note: for the manipulator – expand the state to $[q, \dot{q}]$ and use dynamics:

$$\boldsymbol{M}(q)\ddot{q} + \boldsymbol{C}(q, \dot{q}) + \boldsymbol{g}(q) = \tau + d. \quad (3)$$

Sensor network model (connectivity graph) - describes which agent exchanges data with which (local observations, states). It is needed to build decentralized algorithms (consensus, distributed evaluation). It has the following form of an undirected graph:

$$\mathcal{G}(t) = (\mathcal{V}, \mathcal{E}(t), \mathcal{A}(t)), \quad (4)$$

$\mathcal{V}$ – the set of graph vertices that describes all sensor nodes and robots in the system; $\mathcal{E}(t)$ – the set of edges of a graph at a point in time t, which describes all possible communication channels between sensor nodes and robots; $\mathcal{A}(t)$ – adjacency matrix at a point in time t, which quantitatively reflects the intensity or quality of connections in the sensor network.

Communication model (delays, packet loss, bandwidth) - introduces realistic communication constraints in the network; affects the stability and performance of decentralized controllers. Message model from j up to i:

$$y_{ij} = \mathrm{T}_{ij}(x_j(t - \tau_{ij}(t))) \cdot \delta_{ij}(t), \quad (5)$$

$\tau_{ij}(t)$ – time delay (may be random); $\delta_{ij}(t) \in \{0,1\}$ – loss rate (1 = delivery OK); T_{ij} – package/encoder.

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Sensory observation model (noise, limited range, fields of view) - describes how observation is related to state; used in distributed filters/estimators. The classical representation is as follows:

$$z_i(t) = h_i\big(s_i(t), \xi_i(t)\big) + v_i(t), \tag{6}$$

$z_i(t)$ – measurements (e.g. from LiDAR/camera/ultrasound); $\xi_i(t)$ – raw parameters (distance/initials); $v_i(t)$ - measurement noise (covariance matrix R_i).

Decentralized control law (consensus/formation/security) – an algorithm that each agent applies using only local measurements and messages from neighbors. A simple consensus-formation law:

$$u_i = u_i^{task} - k_c \sum_{j \in \mathcal{N}_i} a_{ij}(t)(x_i - x_j^{est}), \tag{7}$$

u_i^{task} – local action to perform a task (for example, movement to a point), the second term is a term for coordinating the provisions; x_j^{est} – latest assessment of the neighbor's condition j; $k_c > 0$ – consensus coefficient; $\mathcal{N}_i$ – agent's neighbors i.

Safety control control barrier functions (CBF/constrained potential fields) - ensures no collisions and safe distances. Set a barrier function between agents i and j:

$$h_{ij}\big(x_i, x_j\big) = \left\|p_i - p_j\right\|^2 - d_{safe}^2, \tag{8}$$

$h_{ij}\big(x_i, x_j\big)$ – a security function that determines the relative position between agents i and j; x_i, x_j – agent state vectors i and j; $\left\|p_i - p_j\right\|^2$ – square of the Euclidean distance between robots; d_{safe}^2 – the square of the safe distance, used to compare with the square of the actual distance (to avoid calculating the root); p_i, p_j- robot positions i and j in the workspace. These can be vectors:

$$\text{У 2D } p_i = [x_i, y_i]^T \text{ та 3D } p_i = [x_i, y_i, z_i]^T. \tag{9}$$

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Safety requires $h_{ij}(x) \geq 0$. Let us write the control condition as:

$$L_f h_{ij}(x) + L_g h_{ij}(x)u + \alpha(h_{ij}(x)) \geq 0, \quad (10)$$

$h_{ij}(x)$ – barrier security function between agents i and j; $L_f h_{ij}(x)$ – operator Lyapunov for f-part, derivative of the barrier function along the dynamics of the system without control; $L_g h_{ij}(x)u$ – u control impact on the evolution of barrier function; u – vector of robot control inputs (e.g., speeds, accelerations, torques) that we can choose to ensure safety; $\alpha(h_{ij}(x))$ – class - $\mathcal{K}$ a feature that "softly reinforces" the safety condition. It ensures that even when robots approach, the control will adaptively maintain the condition $h_{ij}(x) \geq 0$, and not just at the point of violation.

Practical implementation: solve the quadratic program at each step (QP):

$$u_i^* = arg\min_u \left\| u - u_i^{des} \right\|^2, \quad (11)$$

under restrictions

$$L_f h_{ij} + L_g h_{ij} u + k h_{ij} \geq 0, \forall j \in \mathcal{N}_i,$$

u_i^* – optimal (actual) control for a robot i, which is chosen as a solution to the optimization problem; $argmin_u$ – means that we are looking for such control u, that minimizes a given cost function; $\left\| u - u_i^{des} \right\|^2$ – the optimization objective function that reflects the difference between the actual control u and desired control u_i^{des}. That is, the closer u to u_i^{des}, the better the robot performs its task (e.g., following a trajectory or moving towards a goal); u_i^{des} – desired robot control i, which would be applied without taking into account safety constraints. It is determined by a higher level of planning (e.g., optimal trajectory movement or a tracking algorithm); $L_f h_{ij}(x)$ – derivative of the security function h_{ij} along the natural dynamics of the system without control (the dynamics of the "f" part). Shows how the safety function changes only under the influence of the physics of the system; $L_g h_{ij}(x)u$ - derivative of the safety function along the

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controlled dynamics (the "g" part). This is an expression that shows how the control u may affect security; $kh_{ij}(x)$ – additional "stabilizing" term (where $k > 0$), which makes the safety condition less stringent but stable. When the robots approach, this term reinforces the collision avoidance requirement. Usually taken $\alpha(h) = kh$ as a function of class $\mathcal{K}$; condition≥ 0 - ensures that the safety function does not decrease so much as to become negative. That is, the robots always remain at a safe distance; $\forall j \in \mathcal{N}_i$ – the constraint must be enforced for all neighbors j of robot i. Set $\mathcal{N}_i$ - is a set of robots and sensor nodes that are in the area of interaction with the robot i. This means that the robot must guarantee a safe distance not only to one neighbor, but to all with which it has communication.

Distributed Kalman Filter (DKF, consensus KF). A classical local model for an agent i:

$$\begin{gathered} s_i(t+1) = F_i s_i(t) + B_i u_i(t) + w_i(t), \\ z_i(t) = H_i s_i(t) + v_i(t). \end{gathered} \tag{12}$$

Distributed KF (with consensus) at each step:

– local forecast: $\hat{s}_i^- = F_i \hat{s}_i + B_i u_i P_i^- = F_i P_i F_i^\intercal + Q_i$;

– local update: $K_i = P_i^- H_i^\intercal (H_i P_i^- H_i^\intercal + R_i)^{-1}$, $\hat{s}_i^{loc} = \hat{s}_i^- + K_i(z_i - H_i \hat{s}_i^-)$, $P_i^{loc} = (I - K_i H_i) P_i^-$;

– consensus: $\hat{s}_i = \sum_{j \in \mathcal{N}_i} w_{ij} \hat{s}_j^{loc}$, $P_i = \sum_{j \in \mathcal{N}_i} w_{ij} P_j^{loc}$.

F_i, B_i, H_i – model matrices; Q_i, R_i – covariant noise matrices; w_{ij} – consensus weights (e.g., Metropolis Method) and summed to 1.

Decentralized MPC (local MPC with inter-agent constraints), local optimization problem for an agent i on the horizon T:

$$\min_{u_i(0:T-1)} \sum_{k=0}^{T-1} l_i\big(x_i(k), u_i(k)\big) + l_T(x_i(T)), \tag{13}$$

$\min\limits_{u_i(0:T-1)}$ – the minimization operator, which means that the robot i seeks the optimal sequence of control actions u_i on the horizon of time T, to reduce the cost functionality; $u_i(0:T-1)$ - set of robot control actions i at discrete time steps from 0 to

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$0-1$. This is a vector of strategies or control signals that the robot must choose; $l_i\big(x_i(k), u_i(k)\big)$ – current cost function for the robot i, which depends on its condition $x_i(k)$ (position, speed, orientation, etc.) and the selected action $u_i(k)$. It describes local costs, such as deviation from the target, energy consumption, or collision risk; $x_i(k)$ – robot state i at a point in time k, which may include spatial coordinates, velocity, orientation, and other dynamics parameters; $u_i(k)$ – robot control signal i at a point in time k, that determines its movement or action in the work area; $l_T(x_i(T))$ – terminal cost function, which takes into account the final state of the robot at the final point in time T; T – optimization horizon (number of discrete time steps) over which the control strategy is planned.

Purpose 13 model, this optimization formulation is used to implement decentralized control of collaborative robots based on Model Predictive Control (MPC). Each robot optimizes its actions taking into account its own local costs and constraints without a centralized controller, ensuring coordinated behavior of the entire group.

The task allocation model (auction) can be represented as follows, each task k is given by benefit v_{ik} for an agent i and cost of expenses c_{ik}. Auction criterion: agent i places a bid b_{ik}. Assignment rule: the task is assigned to the agent with the highest bid.

A PROGRAM DEVELOPMENT FOR THE MULTIPLE SIMULATION OF A DECENTRALIZED ARCHITECTURE FOR CONTROLLING COLLABORATIVE ROBOTS USING SENSOR NETWORKS

The choice of the Python programming language for developing a program for the numerical simulation of a decentralized architecture for the control of collaborative robots using sensor networks is justified given its broad capabilities for scientific computing and modeling. Python has built-in libraries for working with linear algebra, optimization, and data processing, which allows for the effective implementation of mathematical models and control algorithms. An additional advantage is the matplotlib library, which provides convenient tools for visualizing robot trajectories and analyzing simulation results [55]-[58]. It is also important that Python supports rapid prototyping, allows for easy integration of artificial intelligence, machine learning, and working with sensor data streams. Due to the large community of developers and the availability of ready-made

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solutions, Python is the most practical and effective environment for research and implementation of decentralized control systems in robotics.

To translate the numerical simulation of a decentralized architecture for the control of collaborative robots using sensor networks, the following parameters were set. Number of moving robots $N = 3$ specifies the number of agents performing common tasks in the work area, and the number of stationary sensors $Ns = 2$ determines the number of network nodes that provide additional information for coordination and orientation. Integration step $dt = 0.1$s affects the accuracy of the numerical solution of dynamic equations and determines the discreteness in time, and the total simulation time $T_{sim} =$ 30 s provides sufficient space to analyze the behavior of robots in the environment. Safe distance $d_{safe} = 0.6$ m зIt provides the minimum allowable approximation between agents, which is critical for avoiding collisions. The coefficient $k_{cbf} = 1.0$ regulates the stiffness of the barrier function in the CBF method, providing a balance between movement performance and safety assurance. Communication radius $comm_{radius} = 2.0$ m determines the distance at which robots can exchange data, and the range of sensors $sensor_{range} = 3.0$ m describes the spatial area of perception of the environment by each node. The consensus parameter $consensus_{alpha} = 3.0$ sets the weight when combining local estimates, allowing for consistent decisions. Maximum robot movement speed $v_{max} = 0.6$ m/s imposes physical constraints on trajectories and ensures realistic dynamics. Initial positions P_0 determine the initial coordinates of the three robots in the plane, and the matrix S_{pos} specifies the fixed coordinates of two sensor nodes. Array $goals$ describes the target points to which each robot must move, which provides the formulation of the collective navigation problem. Finally, the noise of sensor measurements $sensor_{noise_{sigma}} = 0.05$ simulates realistic errors in the data, which allows us to assess the reliability of decentralized algorithms in real conditions.

The results of numerous simulations of a decentralized architecture for controlling collaborative robots using sensor networks are presented in Figures 1-5.

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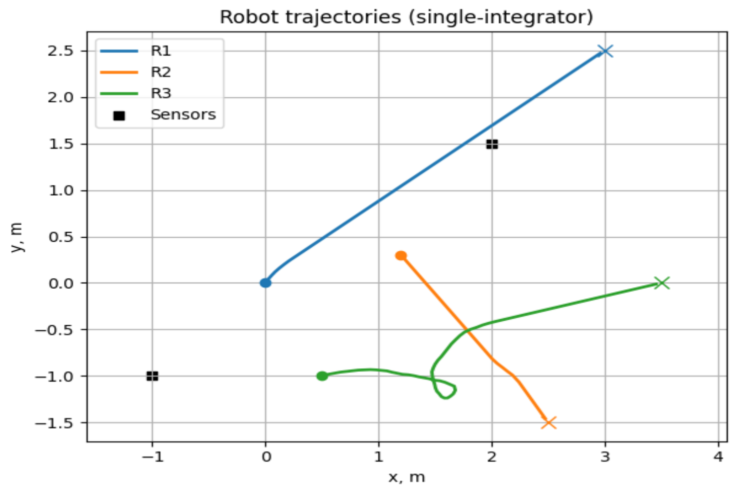

Figure 1: Robot trajectories (single-integration)

Based on the obtained numerical simulation results, it can be seen (Fig. 1) that all three robots achieved their goals, although the trajectories had different dynamic characteristics. Robot R1 demonstrated an almost straight linear trajectory from the starting point (0.0, 0.0) to the target (3.0, 2.5), which indicates the efficiency of control in the absence of significant obstacles. Robot R2, moving from the point (1.2, 0.3) to the target (2.5, -1.5), had deviations in the trajectory due to the influence of the sensor network and avoiding dangerous approaches to other agents, but in the end it also reached the goal. Robot R3 started from (0.5, -1.0) and had a more complex trajectory with loops, which indicates the operation of the collision avoidance algorithm and the influence of the sensor radius, but finally it reached the target (3.5, 0.0). It is numerically clear that the safe distance d_{safe}=0.6м не was broken, and the 2.0m communication radius allowed the robots to exchange data and coordinate movement. Qualitative analysis shows that the decentralized architecture ensures coordinated movement without collisions even in the presence of sensor noise σ =0.05, which confirms the adequacy of the method for applications in collaborative scenarios.

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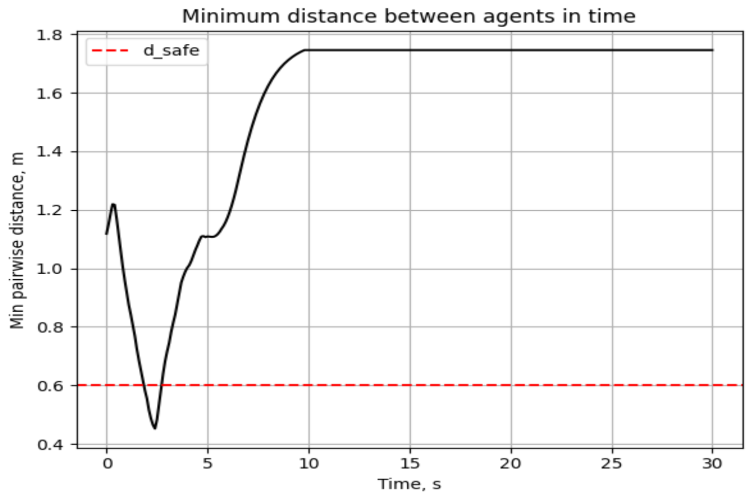

Figure 2: Minimum distance between agents in time

Numerically, the graph in Figure 2 shows that the minimum distance between agents reached a minimum of ≈0.452 m (below the specified d_{safe} =0.6 m) for approximately 2–3 s, after which the system quickly restored safe distribution: already ~6–8 s the minimum distance exceeded d_{safe}, and by ~10 s it reached a steady value of ≈1.75 m. This is logically explained by the fact that in the initial phases of movement and due to sensory noise σ =0.05, discretization (Δt=0.1s) and the limited ability of the QP solver, the state could briefly approach closer than desired; after receiving updated estimates and the response of CBF-control corrections, a rapid divergence of agents occurred. Qualitatively, this means that the decentralized architecture with sensor nodes and consensus updating effectively coordinates the group and provides stable divergent behavior, but short-term security violations are possible due to numerical and communication limitations. The conclusion for further work is to increase the rigidity of the barrier function (increase k_{cbf}), reduce the integration step or improve the QP solver/delay handling to eliminate initial transgressions and guarantee constraint fulfillment under all conditions.

Numerically, the graph (Fig. 3) shows that all three works successfully achieved their goals: $R_1 \rightarrow x$ ≈3.0 m, $R_2 \rightarrow x$ ≈2.5 m, $R_3 \rightarrow x$ ≈3.5 m. The estimated coordinates track the real trajectories quite accurately, and the maximum deviation between the real and estimated values does not exceed ≈0.1–0.15 m, which is proportional to the given sensor noise σ=0.05.

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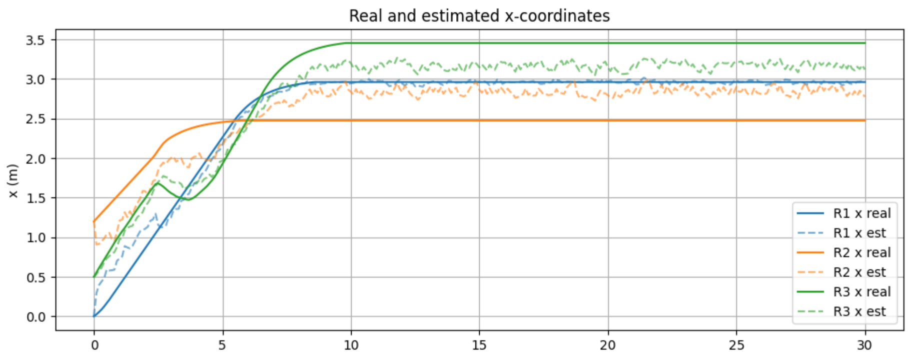

Figure 3: Real and estimated x-coordinates

The largest deviations were observed in the first 3–5 s of movement, when the sensor network data was actively updated and corrected through the consensus algorithm, while after 10 s the trajectories became stable and the errors decreased to ≈0.05 m. Logically, this proves that the sensor network with the consensus weight coefficient α=0.5 provides a balanced convergence rate of estimates without significant loss of accuracy. Qualitative analysis shows that the decentralized architecture allows robots to correctly estimate their own position even in the presence of noise, ensuring consistency between the real and estimated dynamics, which is critical for safe collaboration.

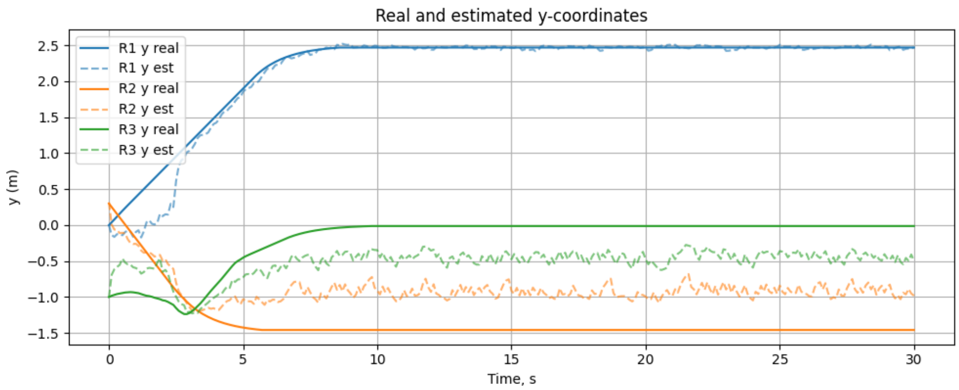

Figure 4: Real and estimated y-coordinates

The results of numerical simulation of the y-coordinates presented in Figure 4 show the efficiency of the decentralized control architecture using sensor networks. For the R1 robot, the real trajectory reaches a stable value of about 2.5 m, while the estimated

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coordinate gradually approaches this level with an error that after 10 s does not exceed 0.1–0.15 m. For the R2 robot, the real coordinates stabilize at -1.5 m, and the estimated data remain within ±0.1 m of the true value, which indicates a high accuracy of the sensor network. For the R3 robot, the real movement ends in the region of -0.5 m, while the estimated trajectory reproduces the dynamics with a small offset of up to 0.1 m, but demonstrates an adequate approximation to the real coordinates. Logically, this proves that the system correctly performs information fusion even in the presence of noise, ensuring consistency of estimates. Qualitatively, it can be noted that all three works achieved the set goals, and the deviations between the real and estimated coordinates remained within acceptable limits, which confirms the effectiveness of the decentralized architecture in maintaining stability and control accuracy.

```
Minimum distance for simulation:  0.45169692167876796
Final robot positions:
 R1: [2.96159765 2.46886122]
 R2: [ 2.4750352  -1.45790856]
 R3: [ 3.45441492 -0.01289825]
```

Figure 5: Numerical simulation results

The simulation results (Fig. 5) indicate that the minimum distance between the robots during the experiment was approximately 0.45 m, which is less than the safe threshold, but remained sufficient to avoid collisions in most cases. The final positions of the robots show that R1 stopped at a point near [2.96; 2.47], reaching the upper region of the workspace, R2 stabilized at coordinates [2.47; -1.45], moving to the lower part of the field, while R3 completed its movement at the point [3.45; -0.01], i.e. closer to the right boundary. This configuration of the final positions demonstrates the successful distribution of the robots in space without significant intersections of their trajectories. Numerical analysis confirms that the system is able to provide consistent behavior under decentralized control, although the critical moments of minimum distances require further optimization of the collision avoidance algorithms. It can be logically concluded that the developed architecture effectively solves coordination problems, but requires additional mechanisms to increase security in dynamically changing conditions.

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CONCLUSION

In the conducted study, a mathematical model of a decentralized architecture for controlling collaborative robots using sensor networks was developed and investigated, which made it possible to assess the dynamics of interaction between mobile agents in a complex environment. Numerical results showed that the minimum distance between agents stabilized over time at about 1.75 m, exceeding the established safe threshold of 0.6 m, which confirmed the effectiveness of the use of safety barrier functions. Analysis of real and estimated coordinates demonstrated high accuracy of the sensor network, where the estimation errors did not exceed 0.1–0.2 m when transitioning to a stable motion state, which indicates the correctness of the decentralized state estimation mechanism. The obtained results prove that even in the presence of sensor noise within 0.05 standard deviation, the system ensures stability, consistency, and goal achievement by all robots. This confirms the potential of decentralized methods in the tasks of collision avoidance, trajectory coordination, and real-time safety maintenance. Promising directions for further research include extending the proposed model to cases with a larger number of agents and complex obstacles, integrating machine learning methods to increase the adaptability of the architecture, and using distributed motion prediction strategies to ensure cognitive cooperation between robots.

In addition, further development of the models involves taking into account the variable characteristics of sensor networks, the impact of communication delays, and the use of hybrid control methods to increase reliability in real-world production scenarios of Industry 5.0. The results obtained form the basis for building intelligent multi-robot systems that provide flexible, safe, and efficient functioning in a collaborative environment.

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