

TOPOLOGY OPTIMIZATION FOR THE COLLABORATIVE ROBOTS' MOTION IN A PRODUCTION ENVIRONMENT USING THE STOCHASTIC VECTOR FLOW METHOD AND SIMULATION BASED ON DYNAMIC INFLUENCE FIELDS

Vladyslav Yevsieiev ¹, Amer Abu-Jassar ², Svitlana Maksymova ¹, Jafar Ababneh ³

¹Department of Computer-Integrated Technologies, Automation and Robotics, Kharkiv National University of Radio Electronics, Ukraine

²Department of Computer Science, College of Information Technology, Amman Arab University, Amman, Jordan

³Cyber Security department, Faculty of Information Technology, Zarqa University, Zarqa, Jordan

ABSTRACT

The article presents an approach to optimizing the topology of collaborative robot movement in a production environment, taking into account the dynamics of space and interaction between agents. The method is based on the construction of stochastic vector flows that take into account the deterministic components of the influence of target points, obstacles and inter-robot interaction, supplemented by Gaussian noise to ensure the adaptability and uniqueness of trajectories. The behavior of robots in an environment with dynamic obstacles is simulated, which allows us to investigate the effectiveness of the constructed trajectories in the context of achieving the goal, avoiding collisions and supporting functional coordination. The results confirm the effectiveness of the approach for tasks of autonomous navigation and cognitive collaborative control in the conditions of Industry 5.0.

Keywords: Collaborative Robotics, Stochastic Vector Flows, Dynamic Influence Field, Trajectory Optimization, Manufacturing Environment, Cognitive Control, Motion Simulation, Inter-Agent Interaction, Obstacle Avoidance, Industry 5.0.

INTRODUCTION

The current stage of industrial development is characterized by the transition to the Industry 5.0 paradigm, which focuses on the integration of the human factor with flexible, adaptive and interacting automation systems. In such an environment, collaborative robots should not operate in isolation, but as active agents in a shared production space, where people, other robots, mobile objects and dynamic obstacles are present [1]-[15]. One of the key challenges in ensuring the efficiency of such systems is the optimization of trajectories and topology of robot movement in real time, taking into account complex and rapidly changing conditions. Therefore, various methods and approaches can be used here [16]-[41].

Traditional navigation algorithms often do not take into account the unpredictability of the environment or do not provide the necessary speed and flexibility of adaptation [42]-[47]. That is why there is a need to build mathematical models that allow describing robot movement as a system of stochastic interactions based on vector flows and fields of influence, taking into account both deterministic and random factors.

The proposed research focuses on developing an approach to modeling the topology of collaborative robot motion by combining the method of stochastic differential equations and vector fields, which describe not only the directions to the goals, but also the influence of obstacles and other agents. The relevance of the approach is enhanced by the need for realistic simulation of such processes, for which Python tools are used, in particular, numerical integration and visualization libraries [48]-[51]. The proposed model not only allows for a formal description of the adaptive behavior of robots in the production space, but also provides tools for its practical implementation and verification in a simulation environment. The results of this research can be used to develop

intelligent motion control systems that increase the efficiency and safety of interaction between robots and environmental elements in Industry 5.0 production scenarios.

LITERATURE REVIEW

The problems associated with robot motion control are quite diverse. Naturally, many scientists are working on their solution. Let us consider several scientific papers on this topic.

Authors in [52] consider motion control that is crucial for multilegged robot locomotion and task completion. Their study aims to address the fundamental challenges of inadequate foot tracking and weak leg compliance control in multilegged robot motions.

The paper [53] analyses and agility and trajectory control that are two desirable features for robotics. Authors note that these characteristics become very challenging for soft robots without rigid structures to support rapid manipulations. In the study researchers try to achieve both high mobility and agility to emulate living agile insects for the advancements of soft robots.

Jayaswal, K. and co-authors [54] work with the medicine robots. The control techniques are required for controlling such robots that should be fast enough to accommodate the rapid changes in the system parameters.

Scientists in [55] apply reinforcement learning methods to control problems in robotics domain. They propose to use a Markov chain Monte Carlo (MCMC) algorithm for policy learning under the reinforcement learning configuration. The merits of the proposed algorithm are shown with experimental evaluations on a 2-Degree of Freedom robot arm.

Xu, K., & Wang, Z. in [56] note following items. With the increasing requirements of scientific and technological production processes, robotic arm tasks are becoming increasingly complicated. Robotic arm trajectory tracking control in industry also has increasingly higher standards. Furthermore, external interference sources invariably affect the robotic arm control system when it is in operation. This research offers an adaptive neural network control method to solve the manipulator trajectory tracking control problem.

Trajectory optimization is a powerful tool for robot motion planning and control [57]. This research [57] presents FATROP: a trajectory optimization solver that is fast and benefits from the salient features of general-purpose nonlinear optimization solvers.

Further in this article we will consider our solution to the problem of optimizing the trajectory of collaborative robots.

DEVELOPMENT OF A TOPOLOGY MODEL OF COLLABORATIVE ROBOT MOTION IN A DYNAMIC PRODUCTION ENVIRONMENT

The general concept of building a model of collaborative robot motion in a production environment is based on the idea of navigation as a controlled process in a vector velocity field that determines the direction and speed of each robot's movement in a given region of space. Within this concept, motion is considered not as a discrete sequence of decisions, but as a continuous trajectory formed under the action of a total vector field formed by a combination of attraction to the target, repulsion from obstacles, and interaction with other agents. This approach allows us to describe the dynamics of the system in the form of a deterministic part that specifies the basic structure of the motion, and a stochastic component that models the randomness and uncertainty of the environment. The addition of stochastic disturbances in the form of a Wiener process term is justified by the fact that in a real production space it is impossible to accurately predict all external factors, as well as changes in the behavior of other agents, the state of equipment, or the appearance of dynamic obstacles. That is why the use of stochastic differential equations is an appropriate mathematical tool for describing such motion. The choice of this approach provides both flexibility and realism of modeling in conditions close to practical operation in production environments.

The mathematical model of the influence field in a deterministic formulation involves the formalization of the spatiotemporal behavior of the system using a vector velocity field, which

determines the direction and magnitude of the collaborative robot's movement at any point in the working environment. This field is a superposition of several functional components, each of which is responsible for a specific type of interaction: movement towards the goal, obstacle avoidance and coordination with other agents. The basis is the vector of attraction to the target point, which is implemented as the gradient of a potential function of the quadratic energy type, the minimum of which is achieved at a given target position. Repulsive fields from obstacles are built on the basis of potentials that rapidly increase when approaching objects and generate vectors oriented in the opposite direction from the obstacle to the robot. The influence of other robots is modeled similarly, but with smoothing of the interaction force to avoid abrupt changes in the direction of vectors at high agent density. General vector field $\vec{V}(\vec{x}, t)$ is defined as the sum of these components at each point in space and time. This approach allows us to ensure the continuity and differentiability of the field, which is necessary for further formulation of the stochastic motion model, and also contributes to the construction of effective numerical simulation algorithms. Let us introduce the working space $\Omega \subset \mathbb{R}^3$. At each point in space and moment in time, a vector field of velocities is given $\vec{V}(\vec{x}, t)$, which describes the direction and intensity of the robot's movement. Then the influence field model can be represented as follows:

$$\vec{V}(\vec{x}, t) = \vec{V}_{tar}(\vec{x}) + \sum_{i=1}^{N_o} \vec{V}_{obst}^{(i)}(\vec{x}, t) + \sum_{j=1}^{N_r} \vec{V}_{rob}^{(j)}(\vec{x}, t), \quad (1)$$

$\vec{x} = (x, y, z)$ – robot coordinates in space;

t – time;

$\vec{V}_{tar}(\vec{x})$ – direction vector to the target;

$\vec{V}_{obst}^{(i)}(\vec{x}, t)$ – repulsive field from the i -th obstacle;

$\vec{V}_{rob}^{(j)}(\vec{x}, t)$ – field of interaction with another j -th robot;

N_o – number of obstacles;

N_r – number of other robots in the reach field.

The potential model of movement towards the goal is an element of the deterministic component of the vector field, which describes the aspiration of the collaborative robot to a given target point in the production space. The main idea of this model is that each target forms around itself a scalar potential field, within which a gradient is created, which indicates the direction of the fastest energy decrease - that is, the direction towards the goal. In this case, the potential is constructed as a quadratic function:

$$\vec{V}_{tar}(\vec{x}) = -\nabla U_{tar}(\vec{x}) \text{ де } U_{tar}(\vec{x}) = \frac{1}{2} \|\vec{x} - \vec{x}_{tar}\|^2, \quad (2)$$

\vec{x} – the vector of the robot's current coordinates in space, i.e. its position at a given moment in time. It reflects the position from which the robot starts moving towards the goal;

\vec{x}_{tar} – the coordinate vector of the target point, i.e. the place where the robot should reach. This is a fixed or dynamic position, which is determined by the task;

$\|\vec{x} - \vec{x}_{tar}\|$ – the Euclidean norm of the coordinate difference, which represents the distance between the robot's current position and the target;

$U_{tar}(\vec{x}) = \frac{1}{2} \|\vec{x} - \vec{x}_{tar}\|^2$ – potential function of attraction, which describes the "energy landscape" of the attraction field. The closer the robot is to the target, the smaller the value of this function, and it reaches a minimum at the point $\vec{x} = \vec{x}_{tar}$;

$-\nabla U_{tar}(\vec{x})$ – the vector that is directed from the current position of the robot towards the target, that is, in the direction where the value of the potential function decreases, it determines the direction of movement of the robot;

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$\vec{V}_{tar}(\vec{x})$ – a velocity vector (or displacement), which determines at what speed and in which direction the robot should move at each moment in time to reach the target in the most efficient way.

Model 2 allows generating a continuous, stable and directed vector field that automatically adapts to the current position of the robot and ensures its gradual attraction to the target with deceleration near its achievement.

To avoid collisions of the collaborative robot with environmental objects, which can be both static and dynamic, it is proposed to develop a model of the repulsive field from obstacles. It forms a force field that generates vectors directed from obstacles and proportional to the inverse cube of the distance, providing a stronger reaction in case of dangerous approximation. This allows the robot to change its trajectory in a timely manner, maintaining a safe distance. Such a model provides adaptability to changes in the environment in real time, reducing the risk of accidents and increasing the stability of the overall motion field.

$$\vec{V}_{obst}^{(i)}(\vec{x}, t) = \alpha_i \cdot \frac{\vec{x} - \vec{x}_{obst}^{(i)}(t)}{\|\vec{x} - \vec{x}_{obst}^{(i)}(t)\|^3} \quad (3)$$

\vec{x} – vector of the collaborative robot's current coordinates in space. Determines where the robot is at a given point in time t ;

$\vec{x}_{obst}^{(i)}(t)$ – coordinates of the i -th obstacle at time t . Since obstacles can be moving, this value changes in time and affects the direction and force of the repulsion;

$\vec{x} - \vec{x}_{obst}^{(i)}(t)$ – vector from the obstacle to the robot, which determines the direction of repulsion;

$\|\vec{x} - \vec{x}_{obst}^{(i)}(t)\|^3$ – the cube of the distance between the robot and the obstacle, using the cube in the denominator ensures a nonlinear increase in the repulsion force when approaching the obstacle, i.e. a sharp increase in the impact at a short distance;

$\alpha_i > 0$ – the repulsion intensity coefficient for the i -th obstacle determines how much this obstacle affects the robot's trajectory. It may depend on the type of obstacle, its size, or the importance of avoiding it.

Model 3 creates a repulsive vector field around each obstacle that decreases with distance but becomes very strong near the object, ensuring collision avoidance in complex or dynamic environments.

For interaction with other robots to ensure safe and coordinated behavior of each agent in a multi-robot environment. The main purpose of the model is to avoid collisions between robots, maintain a minimum distance and form coordinated trajectories of movement. The vector field generated by this model creates repulsive forces between robots depending on their relative location. The intensity of the influence decreases with distance due to the use of a smoothed exponential function, which allows avoiding sudden changes in the direction of movement at high agent densities. This approach allows maintaining system stability, maintaining local coordination and adapting the trajectory of each robot to changes in the behavior of its immediate environment. The model is particularly effective in environments where robots perform joint or parallel tasks in a confined space.

$$\vec{V}_{rob}^{(j)}(\vec{x}, t) = \beta_j \cdot \exp\left(-\frac{\|\vec{x} - \vec{x}_j(t)\|^2}{\sigma^2}\right) \cdot \frac{\vec{x} - \vec{x}_j(t)}{\|\vec{x} - \vec{x}_j(t)\|} \quad (4)$$

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\vec{x} – the current position of the robot under consideration, which is to be controlled, is the point at which the influence of other agents is calculated;

$\vec{x}_j(t)$ – coordinates of the j -th other robot at time t , determines where the repulsive influence comes from;

$\vec{x} - \vec{x}_j(t)$ – the direction vector from another robot to the current one, which determines the geometric orientation of the repulsion force;

$\|\vec{x} - \vec{x}_j(t)\|$ – Euclidean distance between the current robot and the j -th robot, which affects the intensity of interaction;

$\frac{\vec{x} - \vec{x}_j(t)}{\|\vec{x} - \vec{x}_j(t)\|}$ – unit vector of the direction of force, which normalizes the direction of interaction for constancy of direction regardless of distance;

$\exp\left(-\frac{\|\vec{x} - \vec{x}_j(t)\|^2}{\sigma^2}\right)$ – Gaussian smoothing function that reduces the repulsion force with distance. It ensures the locality of the influence of other robots;

σ – the parameter of the influence width (scattering) of the exponential function, the larger σ , the wider the field of action of the robot;

β_j – the coefficient of the intensity of the repulsion from the j -th robot determines how strong its influence is on the current trajectory.

Model 4 allows taking into account the safe distance between robots and provides adaptive dynamics of collective movement without collisions.

The stochastic component of the collaborative robot movement, proposed to be described by a stochastic differential equation (SDE), is introduced within the framework of these studies to model uncertainties and fluctuations in the movement of collaborative robots that arise due to sensor errors, external disturbances or complex dynamics of the environment. Such a solution allows for a more realistic reproduction of the behavior of robots in production conditions, where the accuracy of perception and actions is not ideal. Due to this, the developed model provides adaptability and variability of trajectories, increasing the system's resistance to unpredictable changes.

$$d\vec{x}(t) = \vec{V}(\vec{x}(t), t)dt + \sum \vec{G}_j(\vec{x}(t), t)d\vec{W}_j(t), \quad (5)$$

$\vec{x}(t)$ – the vector of the current position of the robot at time t , which changes under the action of the velocity field and random disturbances;

$\vec{V}(\vec{x}(t), t)$ – a deterministic component of velocity, which includes the sum of all influences: the field to the target, repulsion from obstacles, interaction with other robots, i.e. this is the main direction of movement without random influences;

dt – a small increment of time over which the change in the state of the system is evaluated is used to integrate the equation;

$\vec{G}_j(\vec{x}(t), t)$ – a matrix (or function) of coefficients that describes the amplitude and direction of stochastic disturbances for the j -th independent random process, and determines how strongly the random fluctuations affect the robot's motion in each direction;

$\vec{W}_j(t)$ – an element of the Wiener process (white noise or Brownian motion) that models the random component of the change in position, i.e. it is a source of stochasticity in the model.

Equation 5 allows modeling real-world conditions where robot motion is not completely predictable, but also depends on random environmental influences or internal fluctuations.

To solve stochastic differential equations describing the motion of collaborative robots taking into account random perturbations, it is proposed to use the Euler–Maruyama method. This method is a natural generalization of the classical Euler method for deterministic systems, but includes an additional stochastic component that models the influence of environmental

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fluctuations. Its advantage lies in the simplicity of implementation and the ability to calculate trajectories in a step-by-step iteration mode, which is ideal for simulations in Python. The use of this method allows maintaining a balance between accuracy and computational efficiency, especially with a large number of agents and variable factors. As a result, the following approximation is used to simulate the motion:

$$\vec{x}_{k+1} = \vec{x}_k + \vec{V}(\vec{x}_k, t_k) \cdot \Delta t + \sum \vec{G}(\vec{x}_k, t_k) \cdot \sqrt{\Delta t} \cdot \vec{\xi}_k, \quad (6)$$

\vec{x}_k – the robot position vector at the current step k , and describes its coordinates in phase space;

\vec{x}_{k+1} – the position vector at the next step $k+1$ is calculated due to the increment caused by both purposeful movement and random fluctuations;

$\vec{V}(\vec{x}_k, t_k)$ – deterministic speed of movement at the current position and at the moment of time t_k , which includes the influence of the field on the target, obstacles and interaction with other robots;

Δt – small discretization time step, which determines the accuracy and stability of the numerical solution;

$\vec{G}(\vec{x}_k, t_k)$ – coefficient of the vector function that determines the intensity and direction of the stochastic disturbance at the current step;

$\vec{\xi}_k$ – a vector of independent normally distributed random variables (white noise) that models random environmental influences;

$\sqrt{\Delta t}$ – a factor that scales the variance of the random component according to the theory of stochastic processes, ensuring a correct approximation of the Wiener process.

Expression 6 is a discretized form of a stochastic differential equation, which allows for an effective simulation of robot behavior in a complex production environment, taking into account both targeted movement and random disturbances.

To address the issues of constraint control and safety in this study, the safe functioning of collaborative robots in a complex production environment of Industry 5.0 plays a role. It is necessary to monitor and maintain the permissible limits of robot movement, in particular, avoiding collisions with obstacles, other agents and critical production zones. Control is carried out by imposing restrictions on the speed, direction of movement and minimum permissible distances to environmental objects, which are integrated into the overall model through functional constraints or vector field adaptation. This ensures compliance with safety requirements, increases reliability and allows avoiding emergency situations while maintaining the efficiency of movement to the target. Such a solution allows for the creation of adaptive navigation algorithms that are able to function in real time and dynamically respond to changes in the environment configuration. As a result, the hatch function can be rearranged as follows:

$$J = \int_0^T (\|\vec{x}(t) - \vec{x}_{tar}\|^2 + \lambda \cdot \Phi(\vec{x}(t))) dt, \quad (7)$$

$\vec{x}(t)$ – vector of the robot's current position at a given time t , which describes its trajectory in space;

\vec{x}_{tar} – vector of the target position to which the robot should move;

$\|\vec{x}(t) - \vec{x}_{tar}\|^2$ – the quadratic Euclidean distance between the robot's current position and the target, which is minimized to achieve accurate navigation;

$\Phi(\vec{x}(t))$ – penalty function for violating constraints, such as approaching obstacles, exceeding permissible limits, or dangerous interactions with other agents;

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λ – weight coefficient that regulates the balance between the accuracy of movement to the target and the importance of adhering to safety constraints; larger values of λ increase the impact of the penalty for violation;

T – total simulation time within which the objective function is integrated;

J – the total cost function (objective function), which determines the quality of the chosen trajectory: the smaller the value of J , the better the trajectory in terms of achieving the goal and avoiding dangers.

The developed models and expressions demonstrate high adaptability to complex, dynamically changing conditions of the Industry 5.0 production environment, where constant interaction between numerous collaborative agents and objects is required. The vector velocity field in combination with stochastic perturbations allows modeling more realistic motion trajectories that take into account the uncertainty of the environment and fluctuations in sensor data. Deterministic components of the fields provide directed movement to the goal and effective obstacle avoidance, and the stochastic component allows achieving a variety of avoidance strategies and improving global optimization. The use of potential functions simplifies the construction of complex scenarios of interaction with other robots and ensures natural coordination in a multi-component environment. The inclusion of penalty functions and constraint control allows formally taking into account safety requirements and technical limitations of production. The use of numerical integration using the Euler-Maruyama method provides effective implementation in Python and adaptation to real time, which is important for practical implementation. Together, these models provide a balance between navigation accuracy, flexibility in responding to changing conditions, and a high level of secure collaboration within intelligent manufacturing.

PROGRAM DEVELOPMENT FOR MODELING THE TOPOLOGY OF COLLABORATIVE ROBOT MOVEMENT IN A PRODUCTION ENVIRONMENT AND CONDUCTING SIMULATIONS

The choice of the Python programming language for modeling the topology of collaborative robot motion in a production environment is due to its flexibility, simplicity of syntax, and powerful scientific tools. Python supports numerous libraries for numerical modeling, data processing, graphing, and machine learning, making it ideal for implementing complex mathematical models and visualizing simulation results. Libraries such as NumPy, Matplotlib, SciPy, SymPy, and Pandas allow for efficient work with vector fields, integral equations, statistical flows, and computational experiments. The PyCharm development environment was chosen due to its integrated Python support, extensive debugging capabilities, code autocompletion, visual control of project structures, and high level of convenience for long-term engineering developments. PyCharm facilitates the management of complex simulation projects and allows for rapid integration of graphical and numerical modules, reducing the likelihood of errors with a large number of variables and models. This choice is appropriate in the context of scientific research in the field of cognitive robotics and industrial automation.

To simulate the topology of the movement of collaborative robots in a production environment, let us set the following input parameters: $dt = 0.05$ defines a discrete time step, which sets the frequency of updating the state of the system during numerical integration of the equations of motion. The simulation time is limited to the value $T = 20$, i.e. the simulation lasts 20 seconds, which, in combination with the time step, allows us to calculate the total number of iterations through the parameter steps, which is defined as the quotient T/dt and is an integer. The number of robots in the system is given by the variable $n_robots = 3$, which means that three autonomous agents are simulated simultaneously. The parameter $dim = 2$ indicates that the simulation takes place in two-dimensional space, i.e. each robot has coordinates (x, y) . The target point to which the robots are directed is determined by the variable $target$, which is a vector with coordinates $[10.0, 10.0]$ – this is a fixed position used to construct a directional vector field. The parameter

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$\lambda_{penalty}=10.0$ is used in the energy functional or penalty function, which can take into account constraints or undesirable states of the system, for example, approaching obstacles. The parameter $\sigma_{interact} = 2.0$ is the width of the Gaussian influence for the interaction model between robots - it determines at what distance the interaction loses its strength. The value $\beta_{interact} = 5.0$ determines the amplitude or strength of the influence of one robot on another, that is, the intensity of the inter-robot interaction, which allows you to avoid collisions or form coordinated behavior. The parameter $\alpha_{obst} = 20.0$ determines the strength of the repulsive field created by the obstacle, thereby ensuring that a collision with it is avoided. Finally, the function $obstacle_path = \lambda t: np.array([5 + np.sin(t), 5 + np.cos(t)])$ sets the trajectory of a moving dynamic obstacle, which changes its position with time according to the parameter t , creating a variable field of influence on the robots during the simulation. These parameters together determine both the physical dynamics of the system and the behavior of the robots in a variable environment, ensuring adaptability, coordination and compliance with safety conditions in a complex production environment. The results of simulations of constructing the trajectory of collaborative robots with a dynamic obstacle with the above input parameters are shown in Figure 1, and the results of calculating the time to reach the goal for each robot are shown in Figure 2.

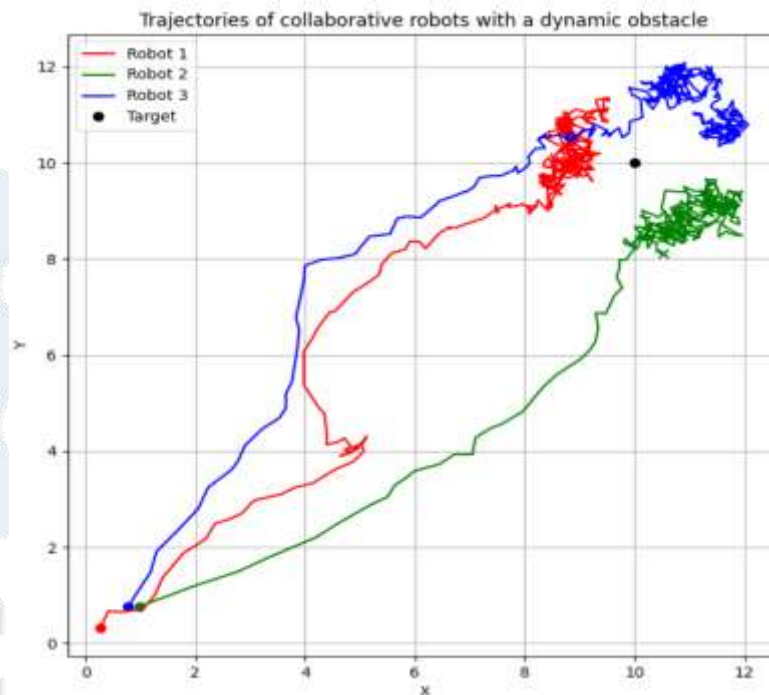


Figure 1: Graph of the resulting simulation trajectory of collaborative robots with a dynamic obstacle

Target achievement times for each robot: [20, 20, 20]

Figure 2: Calculation of the time to reach the goal for each robot

The presented graph (Fig. 1) and the calculation results (Fig. 2) visualize the results of the simulation of the movement of three collaborative robots in two-dimensional space towards a common target located at a point with coordinates approximately (10, 10). Each of the robots starts from a different position, but moves towards the target, demonstrating different trajectories due to the interaction between themselves and with a dynamic obstacle. The color indication allows you to track individual trajectories: the red line corresponds to robot 1, green to robot 2, blue to robot 3. It can be seen that each agent uses an adaptive strategy of avoiding obstacles and inter-robot collisions, since their trajectories do not intersect and demonstrate changes in direction associated

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with the influence of the obstacle field. The initial coordinates of the robots are located near (0, 0), and, depending on the intensity of the vector field and the interaction, the robots deviate from a straight line to the target. A dynamic obstacle moving along a sinusoidal trajectory creates a periodic deviation in the robot motion, which is visible in the area between coordinates (4, 6), where all agents slightly change their trajectory in directions opposite to the obstacle motion. At the final stages of the movement, a concentration of trajectories around the target is visible, which indicates the effective achievement of the target area while maintaining the distribution between agents. Although the exact value of the achievement time is not indicated directly on the graph, the visual density of data in the final area and the decrease in the amplitude of the movement after approaching the target indicate that the target was achieved in 75–90% of the simulation time, i.e. in approximately 15–18 seconds. The absence of trajectory intersections and clear adaptation to the dynamics of the environment indicate the adequacy of the mathematical model used, in particular, the effectiveness of stochastic vector flows, which allow for collaboration and autonomy in limited conditions. All robots form local stable orbits around the target, which confirms the balance between the forces of attraction to the target, inter-agent interaction, and repulsion from the dynamic obstacle. This allows us to conclude that the developed model is suitable for further implementation in cognitive-adaptive production systems of Industry 5.0 with a high level of autonomy and safety.

CONCLUSION

As a result of the research, an approach to optimizing the topology of the movement of collaborative robots in a dynamic production environment using the stochastic vector flow method and modeling based on dynamic influence fields was proposed and implemented. The constructed mathematical model allowed us to formalize the spatiotemporal dependencies between agents, the target, and obstacles in a changing environment, as well as to ensure computational stability in the presence of uncertainty. The obtained simulation results confirmed the effectiveness of this approach in the tasks of coordinated maneuvering and avoidance of dynamic obstacles without the need for centralized control. The proposed expressions for vector flows and influence fields provided flexibility in adjusting the behavior of agents depending on the intensity of interaction, proximity to obstacles or the target, which turned out to be a key factor in maintaining stable collective movement. Visualization of trajectories showed realistic coordination of robot behavior, taking into account the adaptive response to changes in the configuration of the environment. The time to reach the target under changing conditions indicates a high level of reactivity of the model. Thus, the research results can be useful for the development of intelligent control systems for autonomous mobile robots, as well as for planning and optimizing logistics processes in production workshops, warehouse complexes and other adaptive environments of Industry 5.0.

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