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MODEL DEVELOPMENT OF DYNAMIC REPRESENTATION A MODEL DESCRIPTION PARAMETERS FOR THE ENVIRONMENT OF A COLLABORATIVE ROBOT MANIPULATOR WITHIN THE INDUSTRY 5.0 FRAMEWORK

Abstract. The article presents a study on the development of a model for the dynamic representation the environmental description parameters for a collaborative robot manipulator within the Industry 5.0 requirements. The main focus is a mathematical model that allows the robot to quickly adapt to changes in the workspace, ensuring effective and safe interaction with humans. The proposed model takes into account data from various sensor systems, such as lidars, cameras, and ultrasonic sensors, to continuously update information about the environment. The study also considers algorithms that optimize the process of data collection and processing to improve the accuracy of prediction and response of the robot. The results of the work are aimed at increasing the efficiency of collaborative robots in production environments, improving the level of automation and ensuring harmonious cooperation between humans and machines within modern cyber manufacturing systems.

Keywords: collaborative robot, dynamic representation, environmental model, Industry 5.0, sensor systems, robot manipulator, collaboration security, automation, adaptability, cyber manufacturing systems.

Introduction

In the context of Industry 5.0 development, there is a growing need to integrate humans and robots into a joint working ecosystem, where secure collaboration, effective communication, and adaptability to changing environments are key. Collaborative robotic manipulators that interact with humans must not only perform their tasks with high accuracy but also respond to dynamic changes in the workspace, ensuring safe operations. One of the critical requirements for such systems is the ability of the robot to continuously update the environmental model, including the parameters of moving objects, human actions, and other changes in space [1].

The relevance of the study lies in the need to develop methods for dynamic environmental description for collaborative robots that take into account the current requirements of Industry 5.0. This includes not only the creation of mathematical models and algorithms for predicting changes in the environment, but also their integration with sensor systems to ensure a high level of adaptability. The development of such methods will help to increase the efficiency of robotic systems and their safe cooperation with people, which is a critical factor in modern production environments [2].

The aim of the article is to study and develop a dynamic representation of environmental parameters for robot manipulators, which will create the basis for more efficient integration of robotics into cyber manufacturing systems in accordance with the requirements of Industry 5.0.

Main part

When developing models for dynamic parameter updating in a collaborative industrial robot model, it is necessary to implement mathematical models and algorithms that allow adaptation to changes in the environment or in the system's operation. This can be realized using various approaches, including adaptive control, machine learning, and adaptive filtering algorithms [3].

To dynamically update the workspace$\mathbb{R}^3$, the model of which is presented in [X], it is proposed to use adaptive algorithms to monitor changes in the environment:

$$\mathbb{R}^3(t) = \mathbb{R}^3(t-1) + \Delta\mathbb{R}^3(t), \quad (1)$$

where $\mathbb{R}^3(t)$ - three-dimensional space at a moment in time t;

$\mathbb{R}^3(t-1)$ - three-dimensional space at a moment in time $t-1$, describes the three-dimensional space at the previous moment in time. This is the base point from which changes are calculated.

$\Delta\mathbb{R}^3(t)$ - means the changes in the workspace at a point in time t that can be assessed by sensors or a monitoring system.

That is, it reflects the difference or changes that have occurred in three-dimensional space between the time points $t-1$ and t. These changes can be caused by object movements, changes in security perimeters, or other factors.

The assessment of $\Delta\mathbb{R}^3(t)$ can be performed using various sensors that provide data about the environment. These can be described as follows:

- 3D scanners allow collecting data on the three-dimensional geometry of the environment of a collaborative industrial robot manipulator by comparing the captured data with previous scans to determine changes in the environment, the model of such an assessment can be presented as follows:

$$\Delta\mathbb{R}^3(t) = Data_t^{3D} - Data_{t-1}^{3D}, \quad (2)$$

where $Data_t^{3D}$ - are data received from a 3D scanner at a given moment in time t

$Data_{t-1}^{3D}$ - are data at a previous moment in time $t-1$.

- Light Identification, Detection and Ranging (LIDAR) uses laser pulses to determine the distance to objects and create accurate three-dimensional maps, allows you to analyze data from lidar scanners to determine changes in the location of objects, the model of such an assessment can be presented as follows:

$$\Delta\mathbb{R}^3(t) = Data_t^{LIDAR} - Data_{t-1}^{LIDAR}, \qquad (3)$$

where $Data_t^{LIDAR}$ - are data obtained from LIDAR at a given moment in time t;

$Data_{t-1}^{LIDAR}$ - are data at a previous moment in time $t-1$.

- cameras (2D or 3D) record images or videos to detect objects and their changes in space, allow the use of computer vision and AI methods to track objects and estimate their movements, the model of such an estimate can be presented as follows:

$$\Delta\mathbb{R}^3(t) = Data_t^{cam} - Data_{t-1}^{cam}, \qquad (4)$$

where $Data_t^{cam}$ – position of the object according to the data received from the camera at the moment of time t;

$Data_{t-1}^{cam}$ - the position of the object obtained from the camera at the previous moment in time $t-1$.

- distance sensors (ultrasonic, laser, etc.) ($Sens$) measure the distance to objects in real time, i.e. collect data on changes in distances to objects to assess changes in the environment, the model of such assessment can be presented as follows:

$$\Delta\mathbb{R}^3(t) = Data_t^{Sens} - Data_{t-1}^{Sens}, \qquad (5)$$

where $Data_t^{Sens}$ – distance to the object according to the data received from the sensor at the moment of time t;

$Data_{t-1}^{Sens}$ – the distance to the object obtained from the sensor at the previous moment in time $t-1$.

On the basis of 2.45-2.48, changes in three-dimensional space can be represented as:

$$\begin{gathered}\Delta\mathbb{R}^3(t) = \\ = (Data_t^{3D}, Data_t^{LIDAR}, Data_t^{cam}, Data_t^{Sens}) - \\ -(Data_{t-1}^{3D}, Data_{t-1}^{LIDAR}, Data_{t-1}^{cam}, Data_{t-1}^{Sens}),\end{gathered} \qquad (6)$$

where $Data_t^{3D}, Data_t^{LIDAR}, Data_t^{cam}, Data_t^{Sens}$ - є даними, отриманими від сенсорів на момент часу t;

$Data_{t-1}^{3D}, Data_{t-1}^{LIDAR}, Data_{t-1}^{cam}, Data_{t-1}^{Sens}$ - are data obtained at a previous point in time $t-1$.

Combining these data allows us to adaptively update the description of three-dimensional space, taking into account changes in the environment, and ensure the accuracy and efficiency of the collaborative robot manipulator.

The working area ($\mathbb{D}$) can dynamically change depending on changes in objects in space or changes in security perimeters (Ω_{safe}) and can be described by the following expression:

$$\mathbb{D}(t) = \mathbb{D}(t-1) \cup \Delta\mathbb{D}(t), \qquad (7)$$

where $\mathbb{D}(t)$ - workspace at a given time t, describes the space in which the robot operates, including all objects (Ω_i) and safety perimeters (Ω_{safe}) that may affect its actions.

This can be a limited area in which the manipulator performs a task, taking into account all new objects and changes in the environment;

$\mathbb{D}(t-1)$ - workspace at a time moment $t-1$, describes the working area at the previous time point. This is the base point from which changes are calculated;

$\Delta\mathbb{D}(t)$ - changes in the workspace at a given time, which can be described as new or changed areas of the workspace, i.e., it reflects new objects or changes in existing objects that have appeared or been changed in the workspace between time points $t-1$ and t.

This can be, for example, a new facility, a relocated facility, or a change in security perimeters.

A dynamic workspace ($\mathbb{D}(t)$) can be described as a system that is constantly updated in response to changes in the environment ($\Delta\mathbb{D}(t)$). Updating can occur in real time due to data from sensors and cameras [5-7] that track changes in the environment. As a result $\Delta\mathbb{D}(t)$, within the framework of these studies, it can be represented as follows [4]:

- 3D scanners and lidars collect data about the three-dimensional geometry of the environment, identifying new objects or changes in the location of objects. New information obtained from scanners or lidars can be represented as an addition to the previous zone and can be described as follows:

$$\Delta\mathbb{D}(t) = \Omega_{new}^{3D,LIDAR}, \qquad (8)$$

where $\Omega_{new}^{3D,LIDAR}$ - new objects or changes in the location of objects, obtained from scanners or lidars,

- camera(s) collect images or video to detect new objects or changes in the environment. New or changed objects detected in the images are added to the workspace and can be described as follows:

$$\Delta\mathbb{D}(t) = \Omega_{new}^{cam}, \qquad (9)$$

where Ω_{new}^{cam} - new objects or changes in the location of objects received from the camera;

- distance sensors measure the distance to objects, which allows detecting new objects or changes in their location, new data from distance sensors are added to the working area, and can be described as follows:

$$\Delta\mathbb{D}(t) = \Omega_{new}^{sens}, \qquad (10)$$

where Ω_{new}^{sens} - new objects or changes in the location of objects received from distance sensors;

As a result, the mathematical description of the dynamic work area can be obtained by modernizing expression 7 and using expressions 8-10, the result of this solution is given below:

$$\begin{gathered}\mathbb{D}(t) = \\ = (Data_{t-1}^{3D}, Data_{t-1}^{LIDAR}, Data_{t-1}^{cam}, Data_{t-1}^{Sens} \\ \cup\, \Omega_{new}^{3D,LIDAR}, \Omega_{new}^{cam}, \Omega_{new}^{sens}) \backslash \\ \backslash \text{Removed } (\Omega_{t-1}^{3D,LIDAR}, \Omega_{t-1}^{cam}, \Omega_{t-1}^{sens})\end{gathered} \qquad (11)$$

where $Data_{t-1}^{3D}, Data_{t-1}^{LIDAR}, Data_{t-1}^{cam}, Data_{t-1}^{Sens}$- is the working space of the collaborative robot manipulator at the previous moment in time, all objects and areas that were relevant at the moment $t-1$, formally, this is an extended representation $\mathbb{D}(t-1)$ from expression 7;

$\Omega_{new}^{3D,LIDAR}, \Omega_{new}^{cam}, \Omega_{new}^{sens}$ - are new objects that have been added to the workspace between time $t-1$ and t, as a result, objects have appeared in the workspace and need to be added to the previous zone, formally, this is an extended representation$\Delta\mathbb{D}(t)$ from expression 2.50;

Removed ($\Omega_{t-1}^{3D,LIDAR}, \Omega_{t-1}^{cam}, \Omega_{t-1}^{sens}$) - are objects that were in the workspace earlier (at time $t-1$), but are no longer part of the workspace. This can be because the objects have moved, been deleted, or are no longer relevant.

Based on 11:

$$Data_{t-1}^{3D}, Data_{t-1}^{LIDAR}, Data_{t-1}^{cam}, Data_{t-1}^{Sens} \cup \Omega_{new}^{3D,LIDAR}, \Omega_{new}^{cam}, \Omega_{new}^{sens} -$$

the operation of combining two sets - the previous workspace and the new objects.

This creates an updated set of objects that are in the workspace at the time of t, including new objects, and Removed ($\Omega_{t-1}^{3D,LIDAR}, \Omega_{t-1}^{cam}, \Omega_{t-1}^{sens}$) - the set difference operation removes objects that are no longer part of the workspace.

That is, those objects that have been deleted or are no longer relevant are removed from the result of the merge (with new objects).

Here is an example of how 11 allows you to dynamically update the workspace, adapting it to changes in the environment of the colaborative robot manipulator.

Suppose that the working area of the collaborative robot manipulator at the previous time

$$\mathbb{D}(t-1) = A, B, C$$

has the following objects , and suppose the appearance of $\Omega_{new}^{cam} = \{D, E\}$ that are the new objects that were added to the working area between $t-1$and t, while the object$\{B\}$ left the working area and is no longer part of it. Then, according to 11, a merge is:

$$\{A, B, C\} \cup \{D, E\} = \{A, B, C, D, E\},$$

and a delete is

$$\{A, B, C, D, E\} \setminus \{B\} = \{A, C, D, E\}.$$

Thus, at the moment t, the working area $\mathbb{D}(t)$ will include objects$\{A, C, D, E\}$ excluding objects that have been deleted. The proposed model 11 based on 7 allows us to dynamically update the working area, adapting it to changes in the environment, which is important for the accuracy and safety of collaborative industrial robots.

The model of the dynamics of objects in space is based on the model of objects in space Ω_i, and represents both areas with certain geometric shapes and sizes, the mathematical description of which is given in [5]. To dynamically update the location of objectsΩ_i, it is proposed to use object tracking algorithms. Based on this, the model of the dynamics of objects in the working area of the collisional robot manipulator can be represented as follows:

$$\Omega_i(t) = \Omega_i(t-1) + \Delta\Omega_i(t), \quad (12)$$

where $\Omega_i(t)$ - is the set of objects in space at a moment in time t, the state of objects in space at the current moment in time t, and includes all objects that are in the working area of the colobrative robot manipulator at this moment;

$\Omega_i(t-1)$ - is the set of objects in space at a moment of time $t-1$, is the state of objects in space at the previous moment of time $t-1$, is the base set of objects from which the update starts.

$\Delta\Omega_i(t)$- change in the set of objects for the period from $t-1$ to t, that is, new objects that have appeared or changes in existing objects. In other words, it is the difference between the current and previous state of objects. It can include new objects that have appeared or changes in the properties of existing objects (e.g., moving, resizing, changing state).

Model 12 describes how the set of objects in space is updated over time, allowing for dynamic changes in the environment, such as the addition of new objects or changes to existing ones. To give a mathematical description, the set of objects at time t can be described as $\Omega_i(t) = \{\Omega_c, \Omega_{cy}, \Omega_{co}, \Omega_{cu}, .., \Omega_{qp}\}$, where $\Omega_c, \Omega_{cy}, \Omega_{co}, \Omega_{cu}, .., \Omega_{qp}$ - objects in space that are represented as areas with certain geometric shapes and sizes. Changes in the objects $\Delta\Omega_i(t)$ can be divided into two types of changes: new objects $\Delta\Omega_i^+(t)$ and objects that have been deleted or modified $\Delta\Omega_i^-(t)$. Then:

$$\Delta\Omega_i(t) = \Delta\Omega_i^+(t) \cup \Delta\Omega_i^-(t). \quad (13)$$

Based on 12 and 13, the updated set will look like this:

$$\Omega_i(t) = \Omega_i(t-1) \cup \Delta\Omega_i^+(t) \setminus \Delta\Omega_i^-(t), \quad (14)$$

where $\Omega_i(t-1)$ - a set of objects in space at a given time moment $t-1$, is the state of objects in space at a previous moment in time $t-1$, is the base set of objects from which the update starts;

$\Delta\Omega_i^+(t)$ - new objects in the working area of the collaborative robot manipulator;

$\Delta\Omega_i^-(t)$ - objects that have been deleted or modified in the working area of the collaborative robot manipulator.

For example, let's assume that there are the following objects in our workspace, at the time $t-1$: $\Omega_i(t-1) = \{A, B, C\}$, new objects at time t: $\Delta\Omega_i^+(t) = \{D\}$ and objects deleted or changed at t: $\Delta\Omega_i^-(t) = \{B\}$. Then, in accordance with 14, we have the following updated set:

$$\Omega_i(t) = \{A, B, C\} \cup \{\mathrm{D}\} \setminus \{B\} = \{A, C, D\}. \quad (15)$$

Thus, at time t, the number of objects in the working area of the collaborative robot manipulator will be $\{A, C, D\}$, where object B was deleted, and the object D was added. The proposed model of the dynamics of objects in the working area of a collaborative robot manipulator allows the system to dynamically update the list of objects in the environment, which is important for ensuring the accuracy and relevance of data in robotic systems.

The motion dynamics model $\boldsymbol{q}(t)$is based on the mathematical representation of the position function and can be implemented using adaptive control algorithms that take into account changes in the environment or in the system operation [7]:

$$\boldsymbol{q}(t) = \boldsymbol{q}(t-1) + \Delta\boldsymbol{q}(t) \quad (16)$$

where $\boldsymbol{q}(t)$ - is the state vector of the robot or manipulator at time *t*.

It includes the coordinates of the joints, the position of the end effector, or other system parameters that change over time. If it is represented as a vector of joint positions, it can be described as follows $\boldsymbol{q}(t) = [q_1(t), q_2(t), \dots, q_n(t)]^T$, Where $q_n(t)$ – is the position of the *n*-joint at a time moment t;

$\boldsymbol{q}(t-1)$ - is the vector of the state of the robot or manipulator at the previous time moment *t-1*, and is the base state from which the update is performed;

$\Delta\boldsymbol{q}(t)$ - change in the system state for the period from $t-1$, and may include changes in joint position, velocity, acceleration, or other variables that characterize the dynamics of the system. Mathematical representation $\Delta\boldsymbol{q}(t) = [\Delta q_1(t), \Delta q_2(t), \dots, \Delta q_n(t)]^T$, where $\Delta q_n(t)$ – change in the position of the *n*-joint at a time moment t.

To give an example, let's say we have a robot with three joints. The state vectors of the joints at different times are described as follows:

- at the moment $t-1$: $\boldsymbol{q}(t-1) = [q_1(t-1), q_2(t-1), q_3(t-1)]^T = [1.0, 0.5, -0.3]$ – in radians;

- change of state for the period$\Delta\boldsymbol{q}(t) = [\Delta q_1(t), \Delta q_2(t), \Delta q_3(t)]^T = [0.05, -0.02, 0.1]$ – in radians.

Then the updated state vector in accordance with 16 will be as follows:

$$\boldsymbol{q}(t) = [1.0, 0.5, -0.3]^T + \\ +[0.05, -0.02, 0.1]^T = [1.05, 0.48, -0.2]^T. \quad (17)$$

Let's interpret the results in 17: the position of the first joint changed from 1.0 radians to 1.05 radians; the position of the second joint changed from 0.5 radians to 0.48 radians; the position of the third joint changed from -0.3 radians to -0.2 radians [6].

The proposed formula 16 describes how the system parameters (e.g., the position of the joints or the end effector) change over time.

This is important for modeling the movement of a robot or manipulator, tracking its positions, velocities, and accelerations.

Motion dynamics model $\boldsymbol{\tau}(t)$ should take into account changes in the environment and in the system operation, and is an extension of $\boldsymbol{\tau}$ (2.13) and is as follows:

$$\boldsymbol{\tau}(t) = \boldsymbol{M}(\boldsymbol{q}(t))\ddot{\boldsymbol{q}}(t) + \\ +\boldsymbol{C}(\boldsymbol{q}(t), \dot{\boldsymbol{q}}(t))\dot{\boldsymbol{q}}(t) + \boldsymbol{G}(\boldsymbol{q}(t)) + \Delta\boldsymbol{\tau}(t), \quad (18)$$

where $\boldsymbol{\tau}(t)$ - is a vector of force moments (torsions) applied to the joints of a robot or manipulator at time moment *t*. These are controlling forces or moments that are required to achieve a given state or execute a command;

$\boldsymbol{M}(\boldsymbol{q}(t))$ - the inertia matrix, which depends on the state vector *q(t)*, describes how the inertia of the joints changes depending on their position;

$\ddot{\boldsymbol{q}}(t)$ - is the vector of joint accelerations at time *t*, taking into account the dynamic effects associated with accelerations;

$\boldsymbol{C}(\boldsymbol{q}(t), \dot{\boldsymbol{q}}(t))$ - Coriolis matrix and centrifuge forces and their speeds $\dot{\boldsymbol{q}}(t)$, matrix describes the forces arising from centrifugal effects;

$\dot{\boldsymbol{q}}(t)$ - The vector of joint velocities at a moment in time t, taking into account the Coriolis and centrifuge effects;

$\boldsymbol{G}(\boldsymbol{q}(t))$ - The vector of gravitational forces acting on the robot's joints. Depends on the position of the joints $\boldsymbol{q}(t)$ and describes the forces arising from gravity;

$\Delta\boldsymbol{\tau}(t)$ - changes in force moments, which can be the result of external influences or uncertain changes.

This can include noise, measurement errors, or unaccounted-for dynamic effects, and can look like this for a three-joint robot:

$$\Delta\boldsymbol{\tau}(t) = \begin{bmatrix} noise_1(t) \\ noise_2(t) \\ noise_3(t) \end{bmatrix}, \quad (19)$$

where $noise_1(t)$ - noise or uncertainty change component for the first joint or system element. It can be caused by mechanical malfunctions, measurement errors or other external factors;

$noise_2(t)$ - noise component or uncertainty change for the second joint or system element. It can affect control accuracy and system dynamics;

$noise_3(t)$ - noise component or undefined change for the third joint or system element. It can be the result of additional forces acting on the third component of the system or special operating conditions.

Within the framework of these studies, it is proposed to model the noise as a random process with a normal distribution, which is determined by the average value of μ_i and dispersion σ_i^2.

Formally, this can be presented as:

$$\Delta\boldsymbol{\tau}(t) = \begin{bmatrix} noise_1(t) \\ noise_2(t) \\ noise_3(t) \end{bmatrix}, \quad (20)$$

where $noise_1(t)$ - noise or uncertainty change component for the first joint or system element. It can be caused by mechanical malfunctions, measurement errors or other external factors;

$noise_2(t)$ - noise component or uncertainty change for the second joint or system element. Can affect control accuracy and system dynamics;

$noise_3(t)$ - noise component or uncertainty change for the third joint or system element. It may be the result of additional forces acting on the third system component or special operating conditions.

Noise in this study is considered as a random or statistical change that may have a normal distribution. It is defined as a random process with certain parameters and will be modeled as a random process with a normal distribution.

The normal distribution is defined by the mean μ_i and dispersion σ_i^2. Formally, it can be described as follows:

$$noise_i(t) \sim \mathcal{N}(\mu_i, \sigma_i^2) \quad (21)$$

where μ_i - is the average noise value for the i-th component;

σ_i^2 - is the noise dispersion for the i-th component.

Uncertain variables can be deterministic or random and may include the effects of environmental changes or malfunctions.

They can be described as additional or corrective components that do not have a clear statistical model.

To give an example, let's say there is a manipulator with three joints, and you need to model changes in force moments due to noise [8]:

- noise for the first joint $noise_1(t)$ has a mean of 0 and a dispersion of 0.1. This can be represented as $noise_1(t) \sim \mathcal{N}(0, 0.1^2)$;

- noise for the second joint $noise_2(t)$ has a mean of 0 and a dispertion of 0.05. This can be written as $noise_2(t) \sim \mathcal{N}(0, 0.05^2)$;

- noise for the third joint $noise_3(t)$ has a mean of 0 and a dispertion of 0.2. This can be expressed as $noise_3(t) \sim \mathcal{N}(0, 0.2^2)$.

Thus, the total vector of change in force moments can be represented as in 20, where each component $noise_i(t)$ is a normally distributed random noise with the corresponding parameters.

The mathematical representation of the vector $\Delta\boldsymbol{\tau}(t)$ within the framework of the motion dynamics model $\boldsymbol{\tau}\ (t)$ (21) is important for the accuracy of manipulator control and monitoring.

Its modeling helps in assessing and correcting errors that may occur due to uncertain or random changes in the system [9].

The safety perimeters Ω_{safe} can change depending on new data about objects in the environment or changes in the system operation at time t, so the dynamic model (updating the safety perimeters) can be represented as follows:

$$\Omega_{safe}(t) = \Omega_{safe}(t-1) \cup \Delta\Omega_{safe}, \quad (21)$$

where $\Omega_{safe}(t)$ - safety perimeters at time t, is a set of areas in space that define safety zones around the robot, which may include areas of danger to people and other objects. In this research, it is presented as a set that defines the boundaries where robots should limit their activities to ensure safety;

$\Omega_{safe}(t-1)$ - security perimeters at the previous time t-1, These are the values of security perimeters before the update at time t;

$\Delta\Omega_{safe}$ - changes in security perimeters, which is a set of new zones or changes to existing security zones that need to be considered when updating the security model.

It can include new zones that are added or changes in the size of existing zones.

To give an example, suppose that at time *t-1*, the safety p

erimeters of the manipulator are defined as an area around the robot that includes a radius *(r) - 2* meters. At time t, the safety perimeters may be updated due to new conditions, such as:

- new perimeters, a new safety zone with a radius of 1 meter is added around certain objects in the work area;

- changes in the existing perimeters, the average radius of the safety zone is increased by 0.5 meters.

Mathematically, this can be represented as follows:

- The safety perimeter at time *t-1*, which is equal to *r=2* meters, can be represented as follows:

$$\Omega_{safe}(t-1) = \Omega_{safe}\{r = 2 \text{ meters}\}; \quad (22)$$

- new perimeters or changes, can be described as follows:

$$\Delta\Omega_{safe} = \Omega_{safe}^{new} r = 1\text{meters} \cup \\ \cup\ \Omega_{safe}^{expa} r = 2.5\text{meters}. \quad (23)$$

To obtain the model of the updated security perimeters at time *t*, we substitute models 23 and 24 into 22, and we get the following model:

$$\Omega_{safe}(t) = \Omega_{safe} r = 2\text{meters} \cup \\ \cup\ \Omega_{safe}^{new} r = 1\text{meters} \cup \Omega_{safe}^{expa} r = \\ = 2.5\text{meters}. \quad (24)$$

Model 24 allows to take into account dynamic changes in the security zone, adapting it in accordance with new conditions or security requirements.

The safety perimeters $\Omega_{safe}(t)$ in the context of the collaborative industrial robot model, defines areas or zones around the robot where movement or the robot may be restricted to ensure the safety of people and equipment.

Adaptive communication *u(t)* in the context of a collaborative industrial robot represents the process of exchanging information between the robot system and the operator or other systems, which can change in accordance with changes in the environment or in the system's operation.

In order to consider the function *u(t)* in a dynamic space, it is necessary to describe the state of communication at time t, the mathematical representation of which is given below:

$$u\ (t) = u\ (t-1) + \Delta u\ (t)\ , \quad (25)$$

where $u\ (t)$ - is the state of communication at time t, which is the current set of commands, messages, or information that the robot system exchanges with the operator or other systems. It should be noted that this parameter can include both information about the robot's state and reactions to external commands or conditions;

$u\ (t-1)$ - is the state of communication at the previous time t-1, but it is a set of commands or information that was relevant up to the time t;

$\Delta u\ (t)$ - changes in communication can be: 1) These are new commands or messages that need to be added to the system to accommodate changes in the environment or in the operation of the system. 2) It may include changes in the interaction between the robot and the operator, new instructions to be followed, or new data to be transmitted.

To give an example, suppose that the robot system at time t-1 received and transmitted information about the current position and speed.

At time t, the system adapts to the new conditions, where the operator adds a new command to change the trajectory, and the system needs to report the current battery status.

Then the communication at time t-1 can be represented as follows:

$$u\,(t-1) = \{\text{Position Information, Speed Information}\}. \quad (26)$$

New changes in communication:

$$\Delta u\,(t) = \{\text{Trajectory Change Command, Battery Status Update}\}. \quad (27)$$

Then the updated communication at time t, respectively, 2.67 will be as follows:

$$u\,(t) = \{\text{Position Information, Speed Information, Trajectory Change Command, Battery Status Update}\}. \quad (28)$$

As can be seen from 28, adaptive communication can include mechanisms that allow the system to automatically change communication protocols depending on the context. For example:

- changes in environmental conditions, If the robot detects a new object in the work area, the system can automatically communicate information about the new object to the operator and request confirmation of further action;

- changes in the system operation, if the robot detects a decrease in the battery level, the system can initiate a notification to the operator and possibly suggest switching to an economical mode.

Such solutions allow collaborative robotic manipulators to not only respond to external changes, but also actively communicate with the operator, providing a continuous flow of information necessary for safe and efficient collaboration.

The adaptive learning model $\mathbb{M}(t)$means that the model is constantly updated based on new data or new conditions encountered by the robot manipulator.

This allows the robot to improve its performance and adapt to changes in the environment or operating conditions.

Adaptive learning model $\mathbb{M}(t)$ is as follows:

$$\mathbb{M}(t) = \mathbb{M}(t-1) + \Delta\mathbb{M}(t), \quad (29)$$

where $\mathbb{M}(t)$ - is the state of the trained model at time t, a set of parameters or rules that determine the current level of knowledge or skills of the system. In the context of a robot manipulator, this can be a model that defines how the robot performs certain tasks, including control rules, sensor data processing, object recognition, etc.;

$\mathbb{M}(t-1)$ - is the state of the trained model at time t-1, which is the previous state of the model before any changes were made or additional training was performed. This is the starting point from which the model can change over time;

$\Delta\mathbb{M}(t)$ - changes in training or model updates and may be: 1. New knowledge, skills, or rules that are added to the model as a result of training, adaptation, or learning from new data; 2. Can be the result of learning from new data obtained during operation or the result of optimizing the model for better performance.

To give an example, let's say that a collaborative robot manipulator has initially learned to recognize three main types of objects in the work area.

However, in the course of its work, the robot encounters new objects (12) that need to be recognized or new situations that require changing control rules.

Accordingly, the initial state of the trained model at the time $t-1$ is as follows:

$$\mathbb{M}(t-1) = \Omega_s, \Omega_o, \Omega_t, \quad (30)$$

where Ω_s – the object is recognized as an area with a geometric shape of a cube;

Ω_o - the object is recognized as an area with a geometric shape of a cylinder;

Ω_t - the object is recognized as an area with a geometric shape of a cone.

The robot collected new data and underwent additional training to recognize a new type of object (for example, a parallelepiped (Ω_{rh})) or new rules of behavior when interacting with this object.

Then changes in learning $\Delta\mathbb{M}(t)$ will have the following form:

$$\Delta\mathbb{M}(t) = \Omega_{rh} + \text{ new conduct rules}, \quad (31)$$

where Ω_{rh} - the object recognized as an area with the geometric shape of a rectangular parallelepiped.

Then the updated state of the trained model at time t, for this example, will be as follows:

$$\mathbb{M}(t) = \Omega_s, \Omega_o, \Omega_t + \Omega_{rh} + \text{ new conduct rules}. \quad (32)$$

In this way, the robot manipulator constantly adapts its model based on new knowledge, which allows it to better cope with new situations or objects in the work area.

This can be realized as part of machine learning algorithms that allow the robot to “learn” while working, or through software updates based on feedback from sensors and control systems.

Conclusions

As a result of the study, a model for the dynamic representation of environmental description parameters for a collaborative robot manipulator that meets the requirements of Industry 5.0 was developed.

The developed model allows robotic manipulators to quickly respond to changes in the workspace, ensuring effective and safe cooperation with humans.

The main advantage of this model is the integration of data from various sensor systems, such as lidars, cameras, and ultrasonic sensors, which allows for a complete and accurate picture of the robot's environment in real time.

This makes it possible to work in dynamic environments where there are constant changes, such as moving objects, changing lighting, or unforeseen obstacles.

The model also takes into account the parameters of human behavior, which is a key factor in ensuring safe cooperation between the robot and the operator in a common space.

Thanks to the introduction of algorithms for processing large amounts of data in real time, the system is able to adapt to new conditions without the need to completely rebuild the entire system.

This increases the flexibility and reduces the cost of operating robotic systems in production environments.

It is proposed to implement the developed model in robotic systems used in automated production, where it is important to ensure the integration of robots with other components of the cyber production system.

The use of this model will increase the efficiency of production processes, reduce the accident rate, and ensure safe cooperation between humans and machines. In addition, the implementation of such solutions will help optimize the costs of developing and integrating robotic systems, as the model supports scalability and can be adapted to different use cases.

Promising areas for further research include improving machine learning algorithms to predict changes in the environment even more accurately, as well as integrating artificial intelligence systems to improve the interaction between the robot and the operator.

The implementation of the developed model will help to accelerate automation processes and increase the level of integration of robots into modern cyber production systems of Industry 5.0, where the priority is not only automation but also harmonious cooperation between humans and machines.

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Розробка моделі динамічного представлення параметрів моделі опису навколишнього середовища колоборативного робота маніпулятора в рамках індустрій 5.0

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Анотація. У статті представлено дослідження, присвячене розробці моделі динамічного представлення параметрів опису навколишнього середовища для колоборативного робота-маніпулятора в контексті вимог Індустрії 5.0. Основна увага приділяється створенню математичної моделі, яка дозволяє роботу швидко адаптуватися до змін у робочому просторі, забезпечуючи ефективну і безпечну взаємодію з людиною. Запропонована модель враховує дані з різних сенсорних систем, таких як лідари, камери та ультразвукові датчики, для постійного оновлення інформації про навколишнє середовище. У дослідженні також розглядаються алгоритми, що дозволяють оптимізувати процес збору та обробки даних для підвищення точності прогнозування і реакції робота. Результати роботи спрямовані на підвищення ефективності колоборативних роботів у виробничих умовах, покращення рівня автоматизації та забезпечення гармонійної співпраці між людиною і машиною в межах сучасних кібервиробничих систем.

Ключові слова: колоборативний робот, динамічне представлення, модель навколишнього середовища, Індустрія 5.0, сенсорні системи, робот-маніпулятор, безпека співпраці, автоматизація, адаптивність, кібервиробничі системи.