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# Research of Existing Methods of Representing a Collaborative Robot-Manipulator Environment within the Framework of Cyber-Physical Production Systems

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**Abstract:** The article is devoted to the research of existing methods of representing a collaborative robot-manipulator environment in the context of cyber-physical production systems. The advantages and limitations of various approaches are analyzed, in particular their suitability for dynamic information updating and integration with robotic systems. The results of the study emphasize the importance of choosing appropriate methods to ensure effective interaction between humans and robots, which is relevant within the concept of Industry 5.0.

**Key words:** Industry 5.0, Collaborative Robot, Work Area, Computer Vision, Robot-Manipulator.

## Introduction

In the context of the rapid development of the concept of Industry 5.0, which is aimed at the close integration of people, machines and intelligent systems, the role of collaborative robots is becoming increasingly important [1]-[14]. Industry 5.0 focuses not only on the automation and efficiency of production processes, as it was in Industry 4.0, but also on the humanization of technologies, ensuring sustainable development, as well as the integration of the latest cyber-physical systems that allow optimizing the work of both humans and robots in a shared space [15]-[27]. Collaborative manipulator robots that can work side by side with humans play a key role in this process, which makes the issue of accurate and dynamic description of their environment particularly relevant.

To achieve a high level of interaction and safety in a shared workspace, cyber-physical systems must have the ability to receive and process information about the robot's environment in real time, adapt its behavior to changes in the environment, and ensure the safety of both people and equipment. This task requires the use of reliable and effective methods of representing the environment, which can be integrated into the structure of cyber-physical systems and provide an appropriate level of interaction. Various methods and approaches can be used here [28]-[40]. In the framework of Industry 5.0, where the coexistence of people and robots is becoming the norm, the issue of developing such methods becomes critically important. Traditional approaches to representing the environment, such as kinematic models, point maps, octant trees, and others, have their advantages and disadvantages, which must be taken into account when developing new solutions for collaborative robots.

Understanding and improving these methods will allow not only to increase the efficiency of robots-manipulators, but also to ensure closer integration of robotic systems into the human environment, which is one of the main goals of Industry 5.0. Thus, the study of existing methods of representing the environment of a collaborative manipulator robot is not only theoretically interesting, but also a practically important step on the way to the creation of innovative production systems capable of effective human interaction.

## Related works

Due to the fact that special attention is paid to the creation of safe conditions during collaborative work between a robot and a human, it is necessary to constantly rebuild and update the robot's working environment. New scientific papers are constantly being written on this issue. Let us consider some of them.

A key challenge in intelligent robotics is creating robots that are capable of directly interacting with the world around them to achieve their goals [41]. Researchers in [41] note that learning will be central to such autonomous systems, as the real world contains too much variation for a robot to expect to have an accurate model of its environment, the objects in it, or the skills required to manipulate them, in advance.

Authors in [42] study how visual representations pre-trained on diverse human video data can enable data-efficient learning of downstream robotic manipulation tasks. Concretely, they pre-train a visual representation using the Ego4D human video dataset using a combination of time-contrastive learning, video-language alignment, and an L1 penalty to encourage sparse and compact representations.

Scientists in [43] propose to use Neural Radiance Fields (NeRFs) that have recently emerged as a powerful paradigm for the representation of natural, complex 3D scenes. They propose an algorithm for navigating a robot through a 3D environment represented as a NeRF using only an onboard RGB camera for localization.

If the robot is not aware of the human position and intention, a shared workspace between robots and humans may decrease productivity and lead to human safety issues [44]. The study [44] presents a survey on sensory equipment useful for human detection and action recognition in industrial environments.

Approaches like simultaneous localization and mapping and visual odometry are the most promising solutions to increase localization reliability and availability [45]. This research [45] leads to the main conclusion that, few methods can achieve simultaneously the desired goals of scalability, availability, and accuracy, due to the challenges imposed by these harsh environments.

Simultaneous localization and mapping (SLAM) is the process of constructing a global model of an environment from local observations of it; this is a foundational capability for mobile robots, supporting such core functions as planning, navigation, and control [46].

Thus, we see the huge popularity of questions about constructing the robot's working environment, as well as mapping its position and the position of various objects. Further in this article, we will provide an analysis of several of the most common methods for describing the robot's environment.

## Environment representation methods for collaborative robots research

Representation of the environment for collaborative robots-manipulator (co-robots) is an important aspect for their integration into cyber-physical production systems. The robot's ability to perform tasks safely and efficiently in dynamic and uncertain environments depends on the accuracy and reliability of this representation. In the context of the task of developing a model and a method of dynamic description of a collaborative robot-manipulator environment for cyber-physical production systems, there are several methods, each of which has its own characteristics, advantages and disadvantages. Let's consider each separately:

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- kinematic models are used to describe the relative position and orientation of the robot and objects in the environment. The main tool is the matrices of homogeneous transformations, which allow determining the position and orientation of system elements relative to each other. This approach is simple to implement and very effective for tasks related to determining trajectories and controlling robot motion. The general mathematical representation of the kinematic model is as follows:

$$T = \begin{bmatrix} R & d \\ 0 & 1 \end{bmatrix} \qquad (1)$$

$T$ - matrix of homogeneous transformations;
$R$ - rotation matrix (3x3);
$d$ - displacement vector (3x1).

Features of use, kinematic models are well suited for tasks where it is necessary to accurately control the position of the robot relative to objects in the environment, for example, for object manipulation or interaction with other devices. The advantages include ease of implementation, accuracy in determining the position and orientation, efficiency at a low level of complexity of the environment, and the disadvantages are limited possibilities for modeling complex or dynamic environments where unpredictable changes occur.

- a model based on point cards (Point Cloud Maps), uses 3D points to describe the surfaces of objects in the environment. Points are usually collected using depth sensors such as LIDAR or stereo cameras. This approach allows accurate reproduction of the three-dimensional structure of the environment, which makes it useful in complex environments where high accuracy is required. The general mathematical representation of the method is as follows:

$$P = \{p_i \in R\}, i = 1,2,...N \qquad (2)$$

$R$ – 3D space;
$p_i=[x_i,y_i,z_i]^T$ - coordinates of a point in three-dimensional space;
$N$ – number of points.

A special feature of use is that point cards are effective for tasks related to navigation in complex three-dimensional environments, such as industrial premises with many obstacles. The advantages of this method are the high accuracy of the description of three-dimensional objects, the possibility of working in complex environments with a large number of details, the disadvantages include a large amount of data that requires significant computing resources for processing; difficulty in modeling dynamic changes in the environment.

- octant trees (Octree) are used for efficient storage and processing of three-dimensional data, where space is divided into hierarchically organized cubic regions. Each cube can be divided into eight smaller cubes, which allows an adaptive approach to processing space with different resolutions. The general mathematical representation of the method is as follows:

$$O=\{root, O_1,O_2, ...,O_g\} \qquad (3)$$

*root* – root node,

$O_i$ – child octant trees.

Features of the use of this method is well suited for compression and efficient storage of large volumes of spatial data, which allows for rapid updating of information about the environment in real time. Advantages include efficient use of memory, the ability to dynamically update data, high processing speed compared to point cards, and disadvantages - complexity of implementation, limitations in accuracy when high detail is required, difficulty in working with dynamic objects.

- network (graph) representations, these models describe the environment as a graph, where vertices correspond to certain positions in space, and edges correspond to possible paths between them. This approach is particularly useful for route planning and navigation tasks where it is necessary to determine the optimal robot path between different points. The general mathematical representation of the method is as follows:

$$G=(V,E) \tag{4}$$

$V$ - set of vertices (positions),

$E$ - set of edges (paths between positions).

The features of use include the fact that they are used to plan optimal routes in known or partially known environments, which can be useful for working in dynamic production systems. Advantages include efficiency in path planning tasks, the ability to adapt to changes in the environment, high flexibility, and disadvantages include dependence on the accuracy of initial data, the complexity of modeling very complex or dynamic environments, and potentially a large number of calculations in the case of a large number of nodes.

- voxel-based models (Voxel-based Models), this approach consists in dividing the space into small cubic elements, or voxels, each of which can be either occupied or free. This method allows you to easily model obstacles and analyze possible paths of the robot's movement. The general mathematical representation of the method is as follows:

$$\mathrm{V}(x, y, z) = \begin{cases} 1, if\_voxel\_is\_busy \\ 0, if\_voxel\_is\_free \end{cases} \tag{5}$$

Features of using voxel models are useful for tasks where it is necessary to describe the environment in detail and take into account all possible obstacles in the way of the robot. The advantages include simplicity in identifying obstacles, the possibility of effective use in three-dimensional environments, support for dynamic environment updates, and the disadvantages include the need for large amounts of memory for data storage, potential difficulty in scaling for large environments, and dependence on voxel resolution.

On the basis of the conducted research, we will compare the methods of representing the environment of a collaborative robot-manipulator within the framework of cyber-physical production systems. The results of the comparison of existing methods are presented in Table 1.

**Table 1:** Comparison of methods of representing a collaborative robot-manipulator environment within the framework of cyber-physical production systems

| Method | Features of use | Advantages | Disadvantages |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Kinematic model | It is used to accurately control the position and orientation of the robot in relation to objects in the environment. | Ease of implementation, high accuracy, efficiency in relatively simple environments. | Limited capabilities for complex and dynamic environments. |
| Point Cloud Maps | Description of the 3D structure of the environment using 3D points obtained from depth sensors. | High accuracy, suitable for difficult environments. | A large volume of data, high requirements for computing resources, difficulty in dynamically updating the environment. |
| Octree | It is used for efficient storage and processing of three-dimensional data, adaptive division of space. | Efficient use of memory, fast data update. | Difficulty of implementation, limitations in accuracy at high detail, difficulty of working with dynamic objects. |
| Network (graph) models | Description of the environment in the form of a graph for route planning and robot navigation. | Efficiency in path planning tasks, flexibility, adaptation to environmental changes. | Dependence on data accuracy, difficulty in modeling complex or dynamic environments. |
| Voxel models | Partitioning of space into voxels to describe obstacles and analyze possible paths. | Ease of identification of obstacles, support for dynamic updating of the environment. | Large amount of memory, difficulty scaling for large environments, dependence on resolution. |

On the basis of the obtained results of comparing the advantages and disadvantages of the methods of representing a collaborative robot-manipulator environment of within the framework of cyber-physical production systems, we will construct a combined histogram, which is shown in Figure 1.

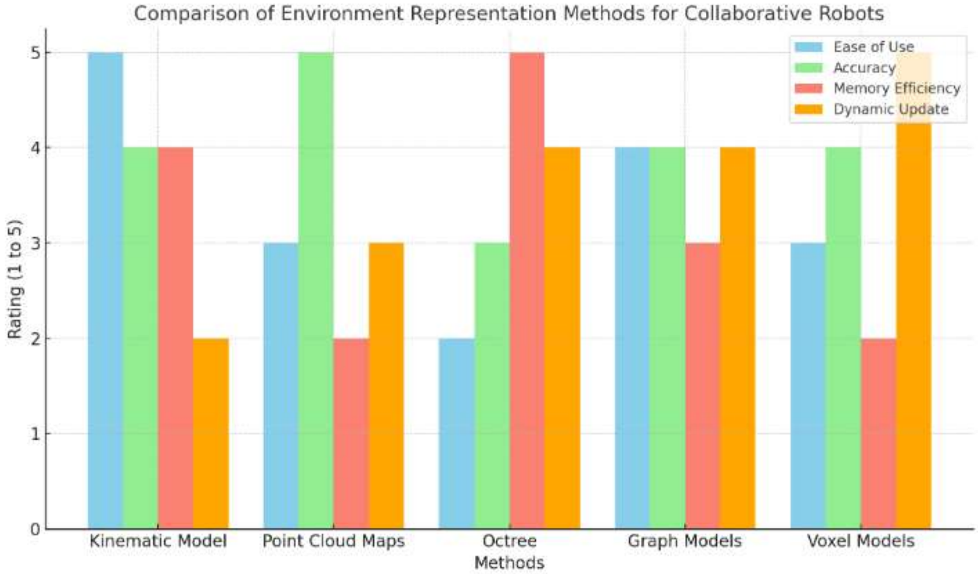


**Figure 1:** Comparison of environment representation methods for collaborative robots

The histogram (Figure 1) shows the ratings for each method based on ease of use, accuracy, memory efficiency, and dynamic update capabilities on a scale of 1 to 5. This visualization helps understand the strengths and weaknesses of each method in the context of developing dynamic descriptions for cyber-physical production systems.

## Conclusion

The study of existing methods of representing a collaborative robot-manipulator environment within the framework of cyber-physical production systems revealed the importance of an accurate and dynamic description of the workspace to ensure effective interaction between a person and a robot. Analysis of different approaches, such as kinematic models, point maps, octant trees, graph models, and voxel models, showed that each of them has its advantages and limitations, which should be considered when designing control systems for collaborative robots. It is important to choose the method that best suits the specific conditions and tasks, providing a balance between accuracy, resource efficiency, and the ability to dynamically update information about the environment.

Further research in this area should focus on the integration of different methods of representing the environment in order to create more versatile and flexible systems that can adapt to changes in real time. This is especially relevant in the context of Industry 5.0, where the emphasis is on close cooperation between people and robots. The use of combined approaches can contribute to increasing the safety and efficiency of cyber-physical systems operating in conditions of constant variability of the production environment. The results of this study create a solid foundation for the further development of technologies for representing the environment and improving the interaction between man and machine in production processes.

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