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METHOD OF PLANNING AND COORDINATION OF ROBOT MOVEMENT USING NEURAL NETWORKS FOR SOLUTION OF DYNAMIC PRODUCTION SCENARIOS

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Abstract**—***The purpose of the study is to develop an approach to planning the trajectory of a robot manipulator using an intelligent system based on neural networks. For this purpose, the work considered the processes of planning and deploying the movement of the robot. The analysis of existing methods of planning the movement of robot manipulators and the review of intelligent control systems provided a comprehensive picture of the current state of this issue. A system is proposed that can perceive the environment and controls the movement of the robot by generating correct control commands. For this purpose, 3 tasks were solved, namely, the analysis of the environment in order to determine its features, the determination of the trajectory in order to neutralize the collision, and the determination of controlled influences for the executive bodies in order to implement the movement. The functionality and structure of the neural network for solving each of the tasks is proposed. The proposed approach is compared with existing approaches on key parameters, such as the execution time of the planned movement and the time of calculating the movement trajectory. The results confirmed that the use of neural network to optimize the trajectory and dynamic prediction to avoid obstacles significantly increased the adaptability of the system to the changing conditions of the production environment, which opens up new opportunities for improving automated processes and providing optimal conditions for the functioning of manipulator robots in real-time.*

Index Terms—Machine learning; neural networks; motion planning system; intelligent system.

I. INTRODUCTION

Modern requirements for automated systems require the development of new motion planning methods to ensure the accuracy and optimality of robot actions in dynamic production conditions, as existing approaches often have limitations and are unable to provide flexibility in solving dynamic production scenarios This need is caused by the dynamism of the production environment where robots have to function.

Existing methods using optimization and heuristic search methods often have limitations, as they lack flexibility and do not guarantee the optimality and accuracy of robot actions in changing conditions. This is due to the fact that traditional methods based on optimization and heuristic search algorithms are not without drawbacks. They usually use a large number of intermediate points, which requires additional processing and complicates their practical application. In addition, such methods do not take into account dynamic changes in the production environment, such as deformations of robot components or changing operating conditions. This can lead to collisions with dynamic obstacles, which poses risks to robots, people and the environment.

For example, due to the deformation of structural elements, one robot may collide with another if it does not enter the common area in time or is delayed. This highlights the urgent need for motion planning methods that take into account the dynamic changes in the production environment.

The development of such methods is of great practical importance. Their implementation will ensure the safe and effective use of robots in dynamic environments where they must interact with other robots and surrounding objects.

Motion planning taking into account dynamic changes opens the way to increasing the accuracy and efficiency of robots. This will lead to better performance of tasks, saving resources and increasing productivity. Also, this method will reduce the risk of collisions, as the probability of emergency situations will be significantly reduced due to better traffic planning.

As a result, this will lead to the expansion of the spheres of use of robots. Because the ability to adapt to dynamic changes will make robots more versatile and allow them to be used in a wider range of tasks. Therefore, there is a problem of developing a method of planning robot movement with the possibility of taking into account changes in dynamic production scenarios. The results of this research are needed in practice, because they determine the possibility of safe and effective use of robots in conditions where they must interact with dynamic surrounding objects, for example, other robots.

II. PROBLEM STATEMENT

Robotic systems with a high degree of freedom face the problem of a large solution space when planning motion. The non-linearity of the robot's working environment makes this task even more difficult [1].

In the analysis of traditional robot motion planning methods, key techniques such as geometric trajectory planning, inverse kinematics method, dynamic programming, and random positions and optimization methods should be addressed.

Geometric trajectory planning determines the movement of the robot based on the geometric characteristics of the workspace. This method allows you to specify the exact position and orientation of the manipulator, but may be limited by the complexity of solving problems for complex user convenience, it has its limitations, particularly in the area of adaptation to changing conditions [2].

The inverse kinematics method is used to determine the input angles or positions of the manipulator to achieve a specific position or trajectory. This method is effective in solving problems for specific points in space, but may lose accuracy in complex problems due to a large number of possible solutions. Also, it is used in most industrial robot control systems [3].

The inverse kinematics method allows you to determine the robot's kinematic parameters based on its position and orientation.

Dynamic programming considers the movement of the manipulator as a sequence of actions with criteria minimization. This method is effective for optimization problems and for planning trajectories, in particular in cases where the dynamic constraints of the robot are important. However, it can be computationally expensive for real time in complex environments, especially with a large number of dimensions of the decision space and complex tasks [4].

Regarding random positions and optimization methods, these approaches often use random points to reduce the number of intermediate points in the trajectories or use optimization methods to reach optimal solutions.

In order to perform a comparative analysis of the above-mentioned approaches, a table should be drawn up in which their main characteristics and differences will be displayed (Table I).

To solve the problem, it is proposed to use intelligent control systems, namely neural networks. Because they play a key role in improving and optimizing the movement of manipulators, because they provide flexibility and adaptability to changing conditions and allow automating and simplifying the calibration processes of moving robot elements, ensuring maximum accuracy and speed of work [5].

For this, it is necessary to create a neural network, which should generate the trajectory of the robot's movement without collisions with dynamic obstacles.

The neural network must use the robot's real motion dynamics and motion trajectory based on the actual motion execution to accurately calculate the robot's actual motions and trajectory. The planned movement of the robot may differ slightly from the actual movement.

All this allows us to state that it is appropriate to conduct a study dedicated to the development of an approach to the creation of an intelligent system for planning the movement of robots.

III. PROBLEM SOLUTION

In order to achieve the set goal, which consists in the development of an intelligent system based on neural networks for planning the trajectory of a robot manipulator, it is worth proposing an approach that takes into account the key aspects of motion optimization and control. The following tasks can be included in this approach:

- the task of analyzing the environment in order to determine its features.
- the task of determining the trajectory in order to neutralize the collision.
- the task of determining controlled influences for executive bodies in order to implement the movement.

Neural networks such as convolutional neural networks, recurrent neural networks, deep neural networks, and autoencoders are best suited for manipulator robot motion planning systems (Fig. 1).

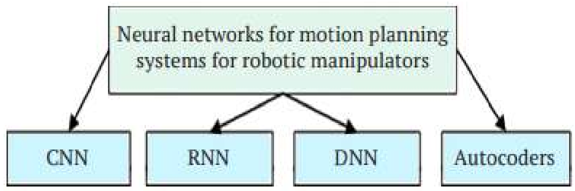

Fig. 1. Neural networks for robotic manipulators

When considering the use of neural networks to solve the described problem, it is important to focus on the analysis and description of architectures that optimally take into account the features of these systems. Neural networks such as convolutional neural networks, recurrent neural networks, and deep neural networks are best suited for motion planning systems of robot manipulators.

Consider a dynamic scene that includes moving objects or a change in the state of objects over time. The architecture of convolutional neural networks is suitable for object recognition. The use of CNN allows effective recognition of objects in real time, which is key to planning the safe movement of the manipulator around objects in the workspace [6].

Dynamic and static scene analysis using the YOLOv7 neural network is one of the effective approaches in the field of computer vision [7]. YOLO is one of the most popular architectures for object detection and localization, and the YOLOv7 version is one of the latest modifications of this architecture (Fig. 2).

TABLE I. COMPARATIVE ANALYSIS OF EXISTING APPROACHES

Approach	Peculiarities	Advantages	Limitations:
Geometric trajectory planning	Determines the movement of the robot according to the geometric characteristics of the workspace	Ensures the exact position and orientation of the robot	Difficulty solving problems for complex configurations
		Convenient management for the user	Limited adaptation to changing conditions
The inverse kinematics method	Defines the input angles or positions of the manipulator to reach a certain point	Effective in solving problems for specific points	Loss of accuracy in complex tasks
		Used in most control systems	A large number of possible solutions in complex problems
Dynamic programming	Considers the movement of the manipulator as a sequence of actions with criteria minimization	Effective for optimization and planning of trajectories	Computationally expensive for real time
		Allows to take into account the dynamic limitations of the robot	Difficulty in use in real time conditions
Random positions and optimization methods	Using random points	Reducing the number of intermediate points in trajectories	Dependence on the initial selection of random points
	Use of optimization methods	Achieving optimal solutions	The need for computing resources, especially for complex tasks

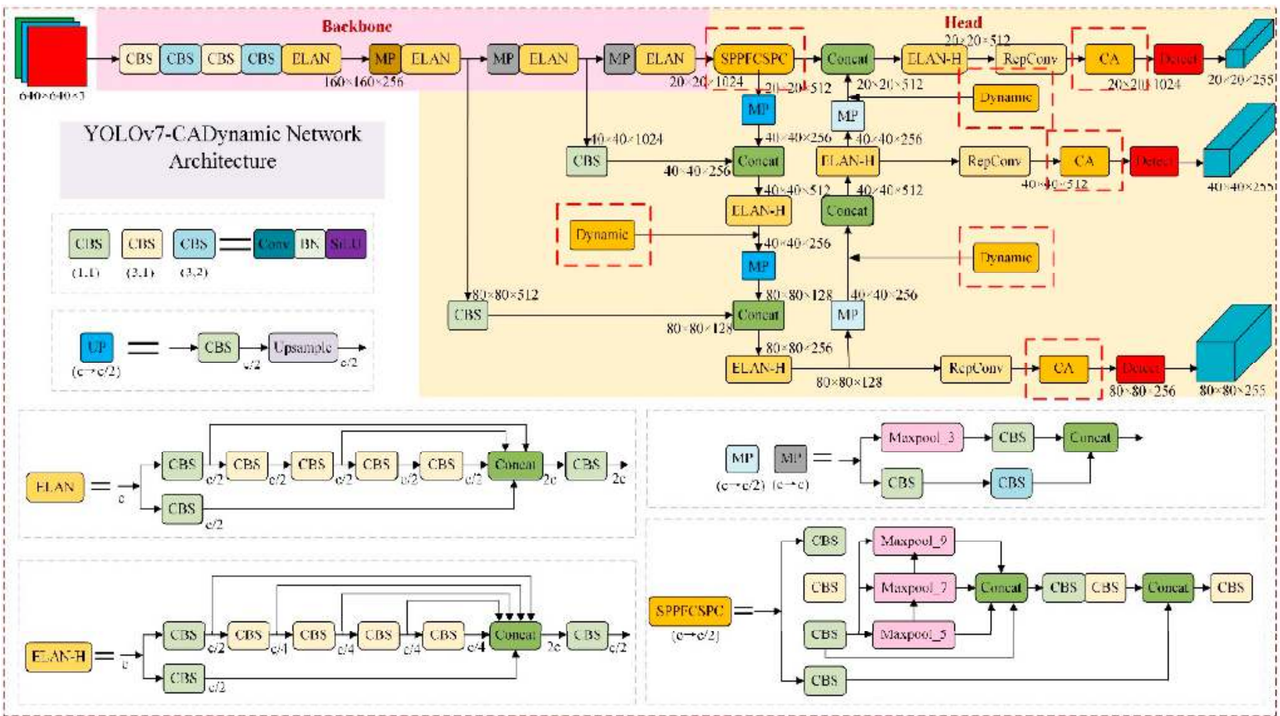

Fig. 2. Structure of the YOLOv7 neural network

After training, the model can be used to automatically detect and track moving objects on video.

However, the analysis of the environment in order to determine their signs is only part of the task, after obtaining the signs, it is necessary to determine the trajectory of the robot's movement in order to neutralize the collision. For this purpose, it is also proposed to use a neural network, which will be aimed at ensuring the safe and efficient operation of the manipulator in an environment with limited spatial conditions. Such a network will improve the safety and performance of the robot, reduce the risk of collisions and avoid damage to obstacles or the robot itself.

To solve the task of determining the trajectory in order to neutralize collisions for the manipulator robot, it is proposed to use a recurrent neural network (RNN). Recurrent Neural Networks (RNN) are used to model motion dynamics (Fig. 3). RNNs are suitable for taking into account time dependencies and modeling the dynamics of manipulator movement, which allows predicting future states of the system [8]. Applying RNN to input data including previous and current states helps to accurately determine the optimal control.

In turn, deep neural networks (Deep Neural Network, DNN) are better used to optimize trajectories (Fig. 4). The use of DNN allows to optimize manipulator movement trajectories, taking into account geometric and dynamic constraints [9]. Deep perceptrons can be used to solve complex path planning problems, taking into account a large number of parameters.

The main idea is that the RNN (Fig. 3) will be used to model the dynamics of the manipulator movement, capable of predicting the future positions of the robot's axes based on the current state, which is performed using Long Short-Term Memory (LSTM) layers (Fig. 5).

Movements planned using this approach correspond to standard movement commands. After generating the trajectory, it is important to determine the control influence and transform it into the commands necessary to execute the movement of the robot manipulator. Thus, the executive input network plays a key role in the motor control system, translating high-level commands into specific control signals.

The structure of the controlled influence detection network includes an input layer that receives high-level commands to determine the desired movement; hidden layers that perform calculations and information processing; the output layer, which generates controlled influences for the implementation of movement; feedback that adapts network parameters based on the output signal and motion results; the parameterization of influences, where the output values can be adapted according to the requirements of executive bodies, such as force or controlled signals (Fig. 6).

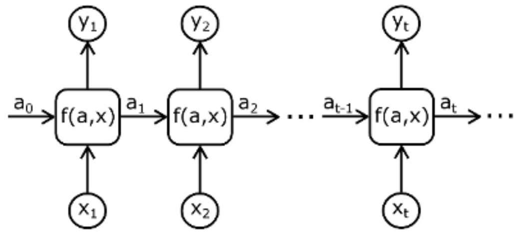

Fig. 3. RNN architecture

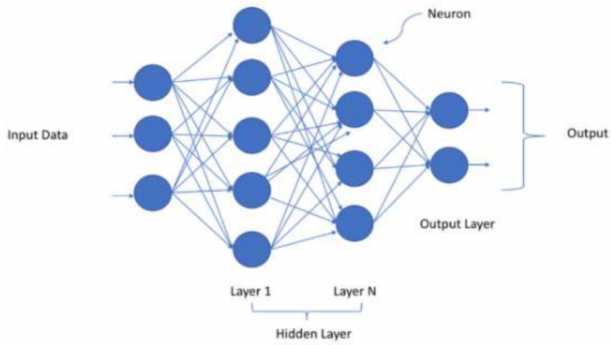

Fig. 4. DNN architecture

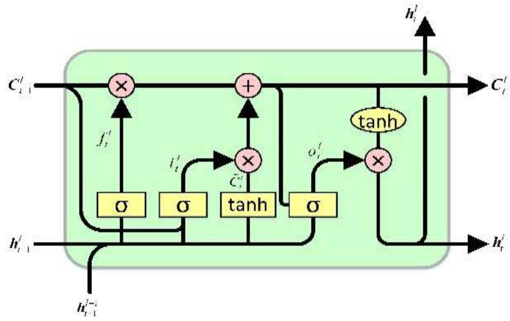

Fig. 5. LSTM architecture

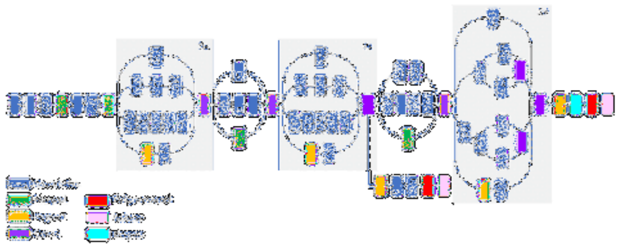

Fig. 6. Schematic diagrams of the managed impacts identification network

IV. RESULTS

We compare the existing robot motion planning algorithm, namely Rapidly Exploring Random Trees

(RRT) with the path generated by the system using the described approach (Table II).

It should be noted that the execution time of the robot's movement trajectory changes significantly due to the different distance between the starting and ending points of the movement.

TABLE II. COMPARATIVE TABLE OF THE EXECUTION TIME OF TRAJECTORIES GENERATED BY THE APPROACH USING YOLOV7 AND RRT

Environment	**The distance between the start and the end**	**Average movement execution time in milliseconds**	
		Proposed approach	***RRT***
A simple static environment	Low	221	212
	Average	422	543
	High	659	836
Complex static environment	Low	291	372
	Average	603	797
	High	732	904
A simple dynamic environment	Low	244	272
	Average	496	581
	High	734	958
Complex dynamic environment	Low	419	462
	Average	765	975
	High	1071	1294

Therefore, let's divide the distance between the starting and ending points of the movement in the test examples into three classes:

1) Small distance (less than 30% of the radius of action of the robot).

2) Average distance (more than 30%, but less than 60% of the radius of action of the robot).

3) Long distance (more than 60% of the radius of the robot).

It is also necessary to pay attention to the fact that the motion of the robot planned by the existing system is significantly different from the motion of the robot proposed by the designed control system. This is because the RRT control algorithm used in the planning phase is quite different from the control algorithm described in the paper, as the RRT planning phase assumes that the joints can reach their maximum acceleration. However, in reality, the robot control system applies only 60% and 45% of the maximum acceleration for the robot axes [8]. Based on this, the average execution time of trajectories generated by the proposed approach is twenty percent faster than RRT.

V. CONCLUSIONS

As a result of the conducted research, the existing data and approaches in the field of robot movement planning were summarized and systematized. The evaluation of existing manipulator motion planning methods and the analysis of intelligent control systems included the results of a comparative study of geometric trajectory planning, dynamic programming, inverse kinematics, random positions, and optimization. This review has highlighted their characteristics, advantages and limitations.

An approach to planning the movement of manipulative robots using an intelligent system was developed, which ensured their ability to self-regulate and adapt to new conditions. The analysis of the proposed approach determined a universal table of execution times of the trajectories, carried out using YOLOv7 and RRT.

In general, the developed approach to motion planning of manipulative robots offers a promising way to achieve high efficiency and flexibility in their use in various production conditions. And for further development in the field of motion planning of manipulative robots, it is recommended to research methods for optimizing system operating parameters, improving machine learning algorithms, and expanding the use of technology in the field of variable production and robotic systems for various tasks.

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В. М. Синєглазов, В. П. Хоцянівський. Метод планування і координації руху робота з використанням нейронних мереж для вирішення динамічних виробничих сценаріїв

Метою дослідження є розробка підходу до планування траєкторії руху робота-маніпулятора за допомогою інтелектуальної системи на основі нейронних мереж. Для цього в роботі розглянуто процеси планування та розгортання руху робота. Аналіз існуючих методів планування руху роботів-маніпуляторів та огляд інтелектуальних систем керування дозволили отримати вичерпну картину сучасного стану цього питання. Пропонується система, яка може сприймати навколишнє середовище та керувати рухом робота, генеруючи правильні команди керування. Для цього було вирішено 3 завдання, а саме: аналіз середовища з метою визначення його особливостей, визначення траєкторії з метою нейтралізації зіткнення та визначення керованих впливів для органів виконавчої влади з метою реалізації рух. Запропоновано функціональні можливості та структуру нейронної мережі для вирішення кожного із завдань. Запропонований підхід порівнюється з існуючими підходами за ключовими параметрами, такими як час виконання запланованого руху та час розрахунку траєкторії руху. Результати підтвердили, що використання нейронної мережі для оптимізації траєкторії та динамічного прогнозування для уникнення перешкод значно підвищило адаптивність системи до мінливих умов виробничого середовища, що відкриває нові можливості для вдосконалення автоматизованих процесів та забезпечення оптимальних умов для функціонування роботів-маніпуляторів в режимі реального часу.

Ключові слова: машинне навчання; нейронні мережі; система планування руху; інтелектуальна система.

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