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# DEVELOPMENT OF A METHOD FOR PLANNING THE MOVEMENT OF A GRIPPING DEVICE FOR A 3-LINK COLLABORATIVE ROBOT MANIPULATOR

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## ABSTRACT

In the modern conditions of industrial automation development and the implementation of Industry 4.0 elements, the problem of safe and effective interaction of collaborative robot manipulators with the environment, including humans, other technical objects and possible obstacles, is of particular relevance. The task of planning the trajectory of the gripping device in conditions of limited workspace, the presence of obstacles and variable production conditions is especially critical, which requires the development of adaptive navigation methods. Given the need to ensure a high level of safety, accuracy and adaptability in the process of controlling robotic systems, the use of artificial intelligence methods and mathematical models capable of providing flexible response to changes in the spatial configuration of the environment is relevant. This article **proposes a method** for planning the movement and avoiding obstacles of the gripping device of a three-link collaborative robot manipulator based on the concept of artificial potential fields (APF).

**The aim of the research** is to create mathematical and algorithmic support for constructing the trajectory of a robotic gripping device, which allows for effective avoidance of collisions with obstacles, while ensuring accurate achievement of the target point in space. **The subject of the research** is the dynamic behavior of a three-link collaborative manipulator in a three-dimensional working environment taking into account the existing static obstacles. The method of artificial potential fields was used as the main research method, in which the attractive force to the target and the repulsive forces from obstacles are formed on the basis of potential functions. To ensure physical reliability and limit the velocity vector, methods of normalizing the velocity and limiting the space to specified limits were used. As part of the modeling, a system of equations of motion was constructed that takes into account the mass of the system, maximum speed and time step of integration.

**The results of the numerical experiment** demonstrated that the developed method provides smooth and safe passage of the trajectory without violating the boundaries of the working area, while the trajectory effectively bypasses obstacles in space and reaches the target point. Visualization of the trajectory in the form of a three-dimensional graph confirms the correctness of the algorithm, which can be applied in practical systems of industrial and service robots. The proposed approach can be the basis for further development of adaptive motion control systems in a changing environment and the use of sensor information fusion methods for processing moving or uncertain obstacles. Thus, the technique can be integrated into real robotic systems operating in cooperation with a person, while ensuring compliance with the principles of safety and efficiency

**Keywords:** Collaborative Robot, Trajectory Planning, Potential Field, Obstacle Avoidance, Gripping Device, Robot Manipulator, Artificial Forces, Modeling, Motion Dynamics, Safe Navigation, Mathematical Modeling, Artificial Potential Fields.

## 1. INTRODUCTION

In the current conditions of robotics intensive development of and collaborative robots implementation in various fields of production, medicine, logistics and service, there is a need to ensure safe and effective interaction between humans and robotic systems [1-3]. The issue of planning the movement of the gripping device of robot manipulators in a complex environment with obstacles is especially relevant, where it is necessary to ensure not only accurate achievement of the goal, but also avoidance of potentially dangerous objects that may appear in the working area in real time [4-6]. Given the complexity of the dynamics of multi-link robots, in particular three-link collaborative manipulators, and the limitations imposed on their movement, there is a need to develop mathematically based methods for planning trajectories that are able to adaptively respond to changes in the environment [7-10]. One of the promising research directions is the use of artificial potential fields (APF) methods, which provide integration of attractive and repulsive forces into a single model, which allows for effective control of the effector trajectory [11-13]. This approach combines simplicity of implementation with high efficiency for real-time tasks and provides the ability to model the intelligent behavior of the system in the presence of dynamic obstacles. The research focuses on the formalization of such a method, its adaptation to the features of the kinematics of a three-link collaborative manipulator and the analysis of its performance in real-world tasks. The relevance of the research is enhanced by the requirements of Industry 5.0, which involves deep interaction between people, robots and artificial intelligence in order to create human-centric, sustainable and flexible production environments [14-18]. The foundations of this concept include the harmonious coexistence of technology and human values, the individualization of solutions, and the use of robotic systems to support creativity, intellectual development, and worker safety [19-21]. In this context, motion planning and obstacle avoidance for a collaborative robot manipulator becomes a key task for ensuring productive and safe interaction within modern cyber-physical production systems.

## 2. LITERATURE REVIEW ON THE RESEARCH TOPIC

In the work of Tian Y., Yue X., Wang L. and Feng Y., a modified trajectory planning method was investigated to reduce vibrations of a collaborative robot during tasks requiring high accuracy. The proposed approach allows to increase the stability of movement and improve the comfort of joint work with a person [22]. However, from the point of view of the research data on the development of a method for planning movement and avoiding obstacles of a gripping device of a 3-link collaborative robot-manipulator using Artificial Potential Fields (APF), the results of this work can be partially used for smoothing the trajectory after building a route, but they are not focused on avoiding obstacles in a dynamic environment. In the article by Zanchettin A. M. et al., the use of genetic algorithms in a simulation environment was proposed to optimize the trajectory of a collaborative robot. This approach allows to form flexible routes taking into account safety and environmental constraints [23]. However, the direct application of genetic algorithms to real-time tasks is difficult, so within the framework of the APF study, the results of this work can be useful only at the stage of comparing the effectiveness of the constructed trajectories.

The work of Proia S. et al. considers the combination of ergonomics, safety and minimum time in trajectory planning, which is especially relevant for collaborative robotics. The authors presented a multi-criteria approach that ensures high quality of interaction between a person and a robot [24]. These ideas can be adapted in the study using APF to form not only safe, but also ergonomic movement, taking into account spatial constraints and the comfort zone of a person.

The article by Pan Y. J. et al. presents a review of modern approaches to planning and controlling the movement of collaborative robots, including methods based on learning, optimization and hybrid systems [25]. The review nature of the publication allows you to identify trends and determine current directions, in particular, the feasibility of using potential fields as a fast adaptive method is confirmed. Therefore, these materials can be used as a theoretical basis for substantiating the effectiveness of APF in a changing environment.

In the work of Wen Y. and Pagilla P., a method for optimal trajectory planning with path constraints and collision avoidance is proposed. The method is focused on ensuring smooth motion and preserving kinematic constraints [26]. The results obtained are relevant to obstacle avoidance tasks, but the method involves significant computational costs, therefore it is less effective for real-time tasks, unlike APF.

Palmieri G. and Scoccia C. in their article considered the problem of dynamic obstacle avoidance for redundant manipulators using a combined planning and control approach. The proposed solution is effective for adapting to changes in the environment, which is similar in purpose to the problem using APF [27]. Thus, their results can be useful for improving the APF model taking into account dynamic objects.

In the work of Liu J. et al. presents a detailed review of motion planning methods in a dynamic environment, in particular, the PRM, RRT, D* and APF algorithms are analyzed [28]. The effectiveness of the APF method is confirmed in cases requiring fast response, which directly supports the direction of the research. This publication is a valuable source for substantiating the choice of method in the proposed study.

Scalera L. et al. investigate trajectory planning for intelligent robotic and mechatronic systems, proposing adaptive and predictive control methods [29]. Although the approaches can be applied to a wide range of tasks, their complexity does not allow these methods to be effectively used in real time without optimization. Therefore, in the context of APF research, these solutions are considered as potentially useful for extending the basic model.

Zhang Z. et al. consider a method for collaborative motion planning with fault-tolerant control for manipulators with redundant degrees of freedom using neurodynamic models [30]. Although this approach provides high reliability, its integration into simple systems like APF is difficult due to the high amount of computation. Direct application is unlikely, but individual concepts can be adapted in future research.

Szczepanski R. et al. in their publication proposed an algorithm for optimal path planning taking into account the speed profile, which allows adapting the robot's movement according to the complexity of the route and avoiding obstacles [31]. This approach is relevant and compatible with methods based on APF, especially when integrating speed controllers into the potential field.

In the work of Zhu N. et al., trajectory planning for cooperative systems with a leader-follower architecture in automated fiber laying tasks [32]. Although the tasks and environment are significantly different, the principles of coordinated motion can be used for further development of the APF model when planning the joint work of several robots.

The general conclusion is that the studied publications confirm the high relevance of trajectory planning and obstacle avoidance tasks in collaborative robotics. Despite the variety of methods - from genetic algorithms to neurodynamic models - the Artificial Potential Fields method remains competitive due to its simplicity, adaptability and ability to respond quickly in a changing environment. This highlights the need for further research to improve the mathematical description and expand the capabilities of APF to work in dynamic, interference-rich environments.

## 3. DEVELOPMENT OF MATHEMATICAL SUPPORT FOR A METHOD OF MOTION PLANNING AND OBSTACLE AVOIDANCE OF A GRIPPING DEVICE BASED ON ARF

The method of artificial potential fields (Artificial Potential Fields, APF) is widely used for planning the trajectories of mobile robots and manipulators, in particular for the task of avoiding obstacles and achieving the goal [11-13]. The general concept of APF is as follows, The potential field is created as a superposition of the attractive potential to the target point and the repulsive potential from the obstacles. The effector moves in the direction of the gradient of decreasing potential energy, as in a physical system.

Let us denote the position (coordinate system) of the end effector in space as a vector:

$$\boldsymbol{x}(t)=\begin{bmatrix}x(t)\\y(t)\\z(t)\end{bmatrix} \tag{1}$$

$x(t)$ - responsible for the position of the effector along the axis $X$; $y(t)$ - position along the axis $Y$; $z(t)$ - along the axis $Z$. $\boldsymbol{x}(t)$ - effector position at a point in time $t$, це is necessary for accurate modeling and planning of its movement when performing manipulation tasks, in particular in the presence of obstacles and restrictions.

- the position of the target point:

$$\boldsymbol{x}_g=\begin{bmatrix}x_g\\y_g\\z_g\end{bmatrix} \tag{2}$$

$x_g$ - target position along the axis $X$; $y_g$ - target position along the axis $Y$; $z_g$ - target position along the axis $Z$. $\boldsymbol{x}_g$ – target position, vector is a reference point when calculating the optimal trajectory, since the end effector must reach this point, taking into account constraints, possible obstacles and criteria for minimizing time or energy consumption.

- obstacle position $i$, determines the coordinates of the $i$-th obstacle center in three-dimensional space relative to the global coordinate system:

$$\boldsymbol{x}_{0_i}=\begin{bmatrix}x_{0_i}\\y_{0_i}\\z_{0_i}\end{bmatrix}, \text{with radius } r_i \tag{3}$$

$x_{0_i}$ – position of the $i$-th obstacle center in three-dimensional space along the axis $X$; $y_{0_i}$ - position of the $i$-th obstacle center in three-dimensional space along the axis $Y$; $z_{0_i}$ - position of the $i$-th obstacle center in three-dimensional space along the axis $Z$. In addition to coordinates, the obstacle is characterized by a radius $r_i$, which determines its size, i.e. the distance from the center to the boundary, which forms a spherical zone of space prohibited for movement. This parameter is used in trajectory planning algorithms to take into account restrictions and ensure the safe passage of the end effector past the obstacle without colliding with it.

Let us describe the attractive potential to the target (Attractive Potential), the potential models the virtual "attractive force" of the end effector to the target point, similar to a spring that pulls the effector to the desired position. The attractive potential to the target is described by the formula:

$$U_{att}(\boldsymbol{x})=\frac{1}{2}k_{att}||\boldsymbol{x}(t)-\boldsymbol{x}_g||^2 \tag{4}$$

$U_{att}(\boldsymbol{x})$ - scalar function of potential energy at point $x$, which determines the magnitude of the attractive potential at the current position of the effector; the closer the effector is to the target, the smaller the value of the function;

$k_{att}$ - the attraction coefficient, which determines the "stiffness" of the field or the force of attraction, the value of this parameter is characterized as follows: the greater its value, the more intensely the field attracts the effector to the target;

$||\boldsymbol{x}(t)-\boldsymbol{x}_g||$ - the Euclidean distance between the current position of the effector $x$ and the position of the target point $\boldsymbol{x}_g$, it determines how far the effector is from the target.

2025, 4(1), pp. 403-413, DOI: 10.5281/zenodo.16617246

Then the gradient (attractive force), defines the vector of force that is directed from the current position of the final effector $\boldsymbol{x}(t)$ towards the target point $\boldsymbol{x}_g$. It is the derivative (gradient) of the attractive potential and is used to generate a control influence on the effector towards the target, which can be described as

$$\boldsymbol{F}_{att}(\boldsymbol{x}) = -\nabla U_{att}(\boldsymbol{x}) = -k_{att}(\boldsymbol{x}(t) - \boldsymbol{x}_g) \tag{5}$$

$\boldsymbol{F}_{att}(\boldsymbol{x})$ - the vector of the force of attraction at point *x* determines the direction and magnitude of the force directed towards the target point. This is the control input used to move the gripping device towards the target.;

$\nabla U_{att}(\boldsymbol{x})$ - gradient of the attractive potential, i.e. a vector indicating the direction of the fastest growth of the potential function. The "minus" sign means that the force is directed in the direction of decreasing potential - towards the target;

$k_{att}$ - the attraction coefficient, which determines the "stiffness" or intensity of the field. A higher value gives a stronger attraction force;

$\boldsymbol{x}(t)$ - the current position of the end effector in space at a point in time $t$;

$\boldsymbol{x}_g$ - target point position;

$\boldsymbol{x}(t) - \boldsymbol{x}_g$ – vector indicating the direction from the target to the current position, and the minus sign provides the direction of the force towards the target.

For each obstacle *i*, at a distance $d_i(\boldsymbol{x}) = ||\boldsymbol{x}(t) - \boldsymbol{x}_{0_i}||$, the Repulsive Potential ($U_{rep_i}(\boldsymbol{x})$) is defined as:

$$U_{rep_i}(\boldsymbol{x}) = \begin{cases} \frac{1}{2} k_{rep} \left( \frac{1}{d_i(x)} - \frac{1}{d_0} \right)^2, if\ d_i(\boldsymbol{x}) \le d_0 \\ 0, \quad if\ d_i(\boldsymbol{x}) > d_0 \end{cases} \tag{6}$$

$k_{rep}$ - repulsion coefficient (positive constant);

$d_0$ - the radius of action of the obstacle (the distance within which the obstacle affects the effector).

The gradient (the repulsive force), can be described as follows:

$$\boldsymbol{F}_{rep_i}(\boldsymbol{x}) = \begin{cases} k_{rep} \left( \frac{1}{d_i(\boldsymbol{x})} - \frac{1}{d_0} \right) \frac{1}{d_i^3(\boldsymbol{x})} (\boldsymbol{x}(t) - \boldsymbol{x}_{0_i}),\ d_i(\boldsymbol{x}) \le d_0 \\ 0,\ d_i(\boldsymbol{x}) > d_0 \end{cases} \tag{7}$$

$\boldsymbol{F}_{rep_i}(\boldsymbol{x})$ - the vector of the repulsion force from the *i*-th obstacle at point *x*, this vector acts in the direction from the obstacle to the end effector, forcing it to change its trajectory to avoid collision

$k_{rep}$ - the repulsion coefficient, which determines the intensity of the force, this value means a stronger repulsive effect, i.e. a greater reaction to approaching an obstacle;

$d_i(\boldsymbol{x})$ - Euclidean distance between the current position of the effector $x(t)$ and $i$-th obstacle $\boldsymbol{x}_{0_i}$ and is calculated by the following expression $d_i(x) = ||\boldsymbol{x}(t) - \boldsymbol{x}_{0_i}||$;

$d_0$ - zone of influence of the obstacle. If the effector is further than $d_0$, the obstacle does not exert a repulsive effect on it, this is the threshold distance that determines the area in which the artificial force field of the obstacle is activated

$\boldsymbol{x}(t)$ - current position of the end effector in space, in time $t$;

$\boldsymbol{x}_{0_i}$ - position of the center of the i-th obstacle in space;

$\frac{1}{d_i(x)} - \frac{1}{d_0}$ – the expression shows how close the effector has approached the boundary of the danger zone $d_0$;

$\boldsymbol{x}(t) - \boldsymbol{x}_{0_i}$ – vector that specifies the direction of force action - from the obstacle center to the effector;

$\frac{1}{d_i^3(x)}$ – a multiplier describing the rate of force increase as the distance to the obstacle decreases, providing a "hard" repulsion in case of danger.

The gradient (expression 7) describes the behavior of the obstacle avoidance system in the APF method, which allows the effector to autonomously respond to approaching obstacles by changing its trajectory of movement, while not violating the main course to the target.

To plan the movement of the collaborative robot's gripping device, it is necessary to carry out a complete description of the potential field (total potential and total force), which is the main element of the APF method.

- total potential:

2025, 4(1), pp. 403-413, DOI: 10.5281/zenodo.16617246

$$U(\boldsymbol{x}) = U_{att}(\boldsymbol{x}) + \sum_{i=1}^{M} U_{rep_i}(\boldsymbol{x}) \tag{8}$$

$U(\boldsymbol{x})$ - total potential, this is a scalar function of position $x$, which determines the energetic "benefit" of the gripping device being at point $x$ in space;

$U_{att}(\boldsymbol{x})$ - attractive potential, we part of the potential field that attracts the gripping device to the target point $\boldsymbol{x}_g$;

$U_{rep_i}(\boldsymbol{x})$ - repulsive potential from an obstacle $i$;

$M$ - number of obstacles in the environment.

Formula 8 allows us to describe the spatial behavior of the manipulator as a result of the interaction of the forces of attraction to the target and the forces of repulsion from the obstacles, forming the optimal route in real time under the constraints.

- total force:

$$\boldsymbol{F}(\boldsymbol{x}) = \boldsymbol{F}_{att}(\boldsymbol{x}) + \sum_{i=1}^{M} \boldsymbol{F}_{rep_i}(\boldsymbol{x}) \tag{9}$$

$\boldsymbol{F}_{att}(\boldsymbol{x})$ - vector of the force of attraction to the target;

$\boldsymbol{F}_{rep_i}(\boldsymbol{x})$ - vectors of repulsion forces from obstacles.

The dynamic model of the effector motion can be described by Newton's second law, provided that its motion is in continuous time, taking into account the mass of the effector $m$:

$$m\ddot{\boldsymbol{x}}(t) = \boldsymbol{F}\big(\boldsymbol{x}(t)\big) \Rightarrow \ddot{\boldsymbol{x}}(t) = \frac{1}{m}\boldsymbol{F}(\boldsymbol{x}(t)) \tag{10}$$

$\boldsymbol{x}(t)$ - position of the end effector (grasping device) at a point in time $t$;

$\ddot{\boldsymbol{x}}(t)$ - acceleration of the effector at time $t$;

$m$ - маса кінцевого ефектора або захватного пристрою, що бере участь у русі і впливає на інерційні властивості системи, чим більша маса, тим менш чутливим буде рух до прикладених сил;

$\boldsymbol{F}\big(\boldsymbol{x}(t)\big)$ - total force acting on the effector at a given time $t$, which is the result of the gradient of the full potential field, takes into account both the forces of attraction to the target and the repulsion from obstacles;

Model (10) allows you to calculate the trajectory of the effector in continuous time based on the applied forces arising in the potential field of the environment. It is necessary for modeling the dynamics of movement, simulation and real control, as well as for implementing smooth and safe movement of the gripping device in the presence of obstacles. Thus, the dynamic model combines kinematics, environmental forces and the mass of the object, which allows you to obtain realistic behavior of the system in the conditions of navigation to the target taking into account the constraints

For simulations, it is proposed to use numerical integration in discrete forms using the Euler method [33,34]:

$$\boldsymbol{v}(t+\Delta t) = \boldsymbol{v}(t) + \frac{1}{m}\boldsymbol{F}(\boldsymbol{x}(t))\Delta t \tag{11}$$

$$\boldsymbol{x}(t+\Delta t) = \boldsymbol{x}(t) + \boldsymbol{v}(t+\Delta t)\Delta t \tag{12}$$

$\boldsymbol{x}(t)$ - end effector position at time $t$;

$\boldsymbol{v}(t)$ - effector speed at time $t$;

$\boldsymbol{F}(\boldsymbol{x}(t))$ - the total force acting on the effector based on potential field gradients (attraction to the target + repulsion from obstacles);

$m$ - end effector mass;

$\Delta t$ - time discretization step (time interval between calculations).

Numerical integration in discrete form according to the Euler method (11-12) allows to approximate the continuous dynamics of the collaborative robot effector motion in digital form for step-by-step calculation of the position and velocity at each subsequent time instant. This approach is widely used in simulations, where the dynamic model is given by differential equations, and the solution must be obtained in the form of a discrete sequence of values.

## 4. DEVELOPMENT OF A PROGRAM FOR SIMULATING ADAPTIVE HIERARCHICAL HIGH-LEVEL CONTROL OF A 3-LEVEL COLLABORATIVE ROBOT-MANIPULATOR

To develop a modeling program for adaptive hierarchical high-level control of a 3-link collaborative robot-manipulator, the Python programming language was chosen due to its high flexibility, simplicity of syntax, and wide support for scientific libraries [35,36]. Python is one of the most popular languages in the field of robotics and machine learning, which provides easy integration with data analysis, simulation, and visualization tools. The use of libraries such as NumPy, Matplotlib, SymPy, SciPy, and ROS packages allows for the effective implementation of both mathematical models of robot dynamics and decision-making algorithms based on hierarchical rules. Python also provides rapid prototyping and allows for easy scaling of the system from a simulation environment to real hardware. With its support for object-oriented programming, Python facilitates the structuring of code by control levels, which ideally corresponds to the principles of hierarchical modeling. In addition, the active Python developer community contributes to the rapid resolution of technical problems and the expansion of functionality using open source. Below are fragments of examples of software implementations of the mathematical description of the obstacle avoidance trajectory planning of the gripping device of a 3-link collaborative robot manipulator based on the ARF method.

```
link_lengths = [0.4, 0.3, 0.3]
joint_limits = [(-np.pi / 2, np.pi / 2)] * 3
dt = 0.1
steps = 500
```

The code snippet sets the basic parameters for simulating the manipulator motion. The link_lengths variable defines the lengths of the three links of the robot manipulator, which is necessary to calculate the position of the end effector. joint_limits sets the limits on the rotation angles of each of the three joints in the range from $-\pi/2$ to $\pi/2$ radians, which simulates physical or design constraints of the system. The dt and steps variables define the time sampling step and the total number of simulation iterations, respectively.

```
k_att = 2.0
k_rep = 1.0
d0 = 0.3
max_speed = 0.08
mass = 1.0
epsilon = 0.02
```

This code fragment sets the parameters of the artificial potential field model to control the movement of the manipulator. The variable k_att determines the force of attraction of the effector to the target point, and k_rep - the intensity of repulsion from obstacles. The parameter d0 sets the zone of influence of obstacles, max_speed limits the maximum speed of the effector movement, and mass is used to calculate acceleration according to Newton's second law. The variable epsilon sets the permissible error of reaching the target, which is used as a criterion for the completion of the movement.

```
x = np.array([0.0, 0.0, 0.0])
v = np.array([0.0, 0.0, 0.0])
x_goal = np.array([0.8, 0.7, 0.6])
```

The presented code fragment initializes the initial conditions for modeling the motion of the end effector of a collaborative robot. The variable x defines the initial position of the effector in three-dimensional space, and v is its initial velocity, which is equal to zero. The variable x_goal specifies the coordinates of the target point to which the effector must reach during the obstacle avoidance trajectory planning task.

```
obstacles = [
    {"center": np.array([0.4, 0.3, 0.3]), "radius": 0.15},
    {"center": np.array([0.6, 0.5, 0.4]), "radius": 0.1},
```

The implemented code fragment defines the parameters of obstacles in the manipulator workspace for the trajectory planning task. Each obstacle is described as a dictionary with the coordinates of the center (center) and radius (radius), which models the spherical zone that the effector must avoid. These obstacles are used when calculating the repulsive force in the potential field to ensure safe obstacle avoidance during movement to the target. This allows the model to respond adaptively to the presence of objects in the environment.

```
def attractive_force(x):
    return -k_att * (x - x_goal)
```

The code fragment defines a function for calculating the force of attraction to a target point in the artificial potential field model. It calculates a force vector that is directed towards the target and proportional to the distance between the current position of the effector and the target. The minus sign means that the force acts in the direction of decreasing this distance, i.e. the effector will be pulled to the desired position. Such an implementation allows you to effectively form a trajectory to the target in continuous space.

2025, 4(1), pp. 403-413, DOI: 10.5281/zenodo.16617246

```
def enforce_workspace_bounds(x):
    return np.clip(x, [0, 0, 0], [1, 1, 1])
def enforce_velocity_limit(v, max_speed):
    norm_v = np.linalg.norm(v)
    if norm_v > max_speed:
        return v / norm_v * max_speed
    return v
```

The presented code fragment is responsible for limiting the space and speed of the end effector. The enforce_workspace_bounds function ensures that the effector coordinates remain within the permissible workspace, limited by a cube from 0 to 1 along each axis. The enforce_velocity_limit function limits the speed so as not to exceed the specified maximum speed, ensuring smooth and physically correct movement. This approach avoids exceeding the physical or safe limits of the manipulator.

```
for step in range(steps):
    F_att = attractive_force(x)
    F_rep = repulsive_force(x)
    F_total = F_att + F_rep
    a = F_total / mass
    v = enforce_velocity_limit(v + a * dt, max_speed)
    x_new = enforce_workspace_bounds(x + v * dt)
    trajectory.append(x_new.copy())
```

This code fragment implements the main cycle of simulation of the end effector motion in a force field consisting of an attractive force towards the target and a repulsive force from obstacles. At each step, the total force, acceleration, velocity are calculated taking into account the constraints, and a new position is updated taking into account the boundaries of the workspace. The calculated position is stored in a list for further trajectory construction. This approach allows you to model the adaptive behavior of the robot in a dynamic environment.

## 5. EXPERIMENTAL STUDIES OF SIMULATION PLANNING OF THE GRABBING DEVICE OF A 3-LINK COLLABORATIVE ROBOT MANIPULATOR BASED ON THE DEVELOPED MATHEMATICAL DESCRIPTION OF THE ARF METHOD

This section discusses the process of conducting experiments to simulate motion planning and obstacle avoidance of the gripping device of a three-link collaborative robot-manipulator based on the developed mathematical description of the ARF (Attractive-Repulsive Field) method. The main goal of experimental modeling is to verify the effectiveness of the algorithm in an artificial environment with the presence of static obstacles and achieve a given goal without collisions. The use of potential fields allows adaptively forming the trajectory of motion by combining the attractive force to the target and the repulsive forces from obstacles. The model was implemented in a three-dimensional limited workspace that simulates the conditions of real interaction of the robot with the environment. During the simulation, kinematic and dynamic parameters such as mass, speed, and the boundaries of the manipulator's working area were taken into account. The simulation results were visualized as a 3D plot of the obstacle avoidance trajectory planning of the gripping device of the 3-link collaborative robot manipulator presented in Figure 1, which demonstrates successful goal achievement without violating constraints. This approach allows us to assess the potential of the ARF method for autonomous trajectory planning in manufacturing and service environments, where safety and accuracy of manipulations are critical.

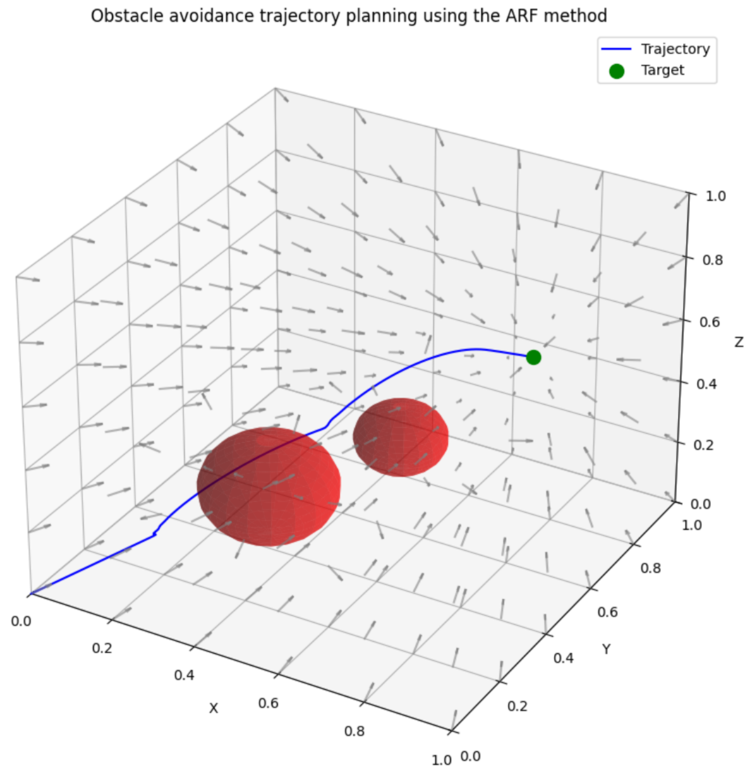


Figure 1 – 3D graph of obstacle avoidance trajectory planning of the gripping device of a 3-link collaborative robot manipulator

During the simulation of obstacle avoidance trajectory planning of the gripping device of a 3-link collaborative robot manipulator, 187 steps were constructed and calculated before the gripping effector reached the end point, fragments of the obtained calculations are given in Table 1.

Table 1. – Fragments of the obtained calculations of obstacle avoidance trajectory planning of the gripping device of a 3-link collaborative robot manipulator.

| | Step | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 30 | 60 | 120 | 160 | 187 |
| Position | 0.00524308<br>0.0045877<br>0.00393231 | 0.15729253<br>0.13763096<br>0.1179694 | 0.1704555<br>0.3381083<br>0.12784162 | 0.38670722<br>0.68511469<br>0.31699031 | 0.61042439<br>0.78241828<br>0.49936899 | 0.78835522<br>0.70561484<br>0.59399928 |
| Velocity | 0.05243084<br>0.04587699<br>0.03932313 | 0.05243084<br>0.04587699<br>0.03932313 | 0.00642466<br>0.07959589<br>0.0048185 | 0.03289381<br>0.05982539<br>0.04170035 | 0.06738389<br>-0.0145892<br>0.04057791 | 0.06546836<br>-0.03105447<br>0.03390448 |
| Attractive Force | 1.6 1.4 1.2 | 1.29590111<br>1.13391347<br>0.97192583 | 1.26037394<br>0.73970258<br>0.94528045 | 0.83316433<br>0.04173569<br>0.57435946 | 0.392628<br>-0.1677544<br>0.2093776 | 0.03638323<br>-0.01744058<br>0.01878233 |
| Repulsive Force | 0. 0. 0 | 0. 0. 0 | -1.17094145<br>0.1533639 -<br>0.87820609 | -0.55137249<br>0.45603266 -<br>0.2219412 | 0.00080504<br>0.06199981<br>0.02081631 | 0. 0. 0 |

The image in Figure 1 and the calculation fragments presented in Table 1 demonstrate the result of 3D modeling of the trajectory of the gripper of a three-link collaborative robot-manipulator using the ARF artificial potential field method for obstacle avoidance. The scene visualizes a 1×1×1 meter workspace, in which two spherical red obstacles with radii of approximately 0.15 m and 0.1 m are placed, as well as a target point marked by a green marker, located at coordinates (0.8, 0.7, 0.6). The starting point of the trajectory is located at coordinates (0.0, 0.0, 0.0), and the path taken by the gripper is marked by a blue curve, demonstrating smooth and safe obstacle avoidance. The direction vectors of the field, visualized as gray arrows, indicate the total action of attractive and repulsive forces that form a gradient navigation map in the environment.

Trajectory analysis indicates effective adaptation to the environment: instead of a direct path to the target, the system avoids obstacles, demonstrating an intelligent response to changing conditions. The minimum distance to a larger obstacle is approximately 0.05 m, which indicates the correct setting of the radius of action of the repulsive force d_0 = 0.3 m and ensuring safe passage. The maximum speed parameter v_max = 0.08 m/s allows you to avoid sudden changes in direction and ensures smooth movement, and the selected mass value m = 1.0 kg stabilizes the dynamic model. The number of simulation steps is 500 with a time step dt = 0.1 s, which corresponds to a total simulation time of 50 seconds - this is quite enough to reach the target taking into account obstacles. The trajectory does not show signs of oscillations or loops near local minima, which indicates a proper ratio of the attraction coefficients k_att = 2.0 and repulsion $k_{rep}$ = 1.0.

In qualitative terms, the resulting trajectory has a characteristic smooth S-shaped shape, which confirms the harmonious balancing between attractive and repulsive forces. This allows collision avoidance even in a dense environment with limited space for maneuver. Thus, the ARF method has demonstrated the ability to provide adaptive high-level control for autonomous navigation tasks in complex conditions, and the simulation results confirm the effectiveness of its application for a three-link collaborative robot manipulator, especially in the context of a real production or service environment.

## 3. CONCLUSION

As a result of the research, a method of planning movement and avoiding obstacles was developed for the gripping device of a 3-link collaborative robot-manipulator based on the Artificial Potential Fields (APF) method. The mathematical support of the method allows forming a vector-directed force field in three-dimensional space, where the target attracts and obstacles repel, thereby ensuring dynamic trajectory construction with collision avoidance. The developed model takes into account the physical limitations of the system, including the maximum speed of movement, the mass of the effector, the discretization step and the dimensions of the workspace. The conducted numerical experiments with visualization in the form of a 3D graph showed that the trajectory successfully adapts to the presence of obstacles, bypasses them while maintaining a minimum distance, maintains smoothness and correctly reaches the given target. The absence of sharp changes in direction confirms the high level of adaptability and safety for further use in conditions of cooperation with a person. The proposed approach has broad prospects for application in industrial, service and mobile robotic systems, where constant adaptation to a changing environment and a guarantee of collision avoidance are required. In the future, this mathematical model can be expanded by integrating it with sensor integration methods (Sensor Fusion), which will allow working with dynamic and uncertain obstacles in real time. This opens up opportunities for creating full-featured intelligent navigation systems for robots that can operate safely and effectively in complex environments, including collaborative manufacturing environments, medical robotics and autonomous logistics systems.

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