engineering proceedings

Proceedings

Virtual Model-Based Trajectory Optimization Algorithm for Aliquoting Robotic System

Larisa Rybak, Dmitry Malyshev and Vladislav Cherkasov *

Belgorod State Technological University named after V.G. Shukhov
* Correspondence: rlbgtu@gmail.com

Abstract: This work is devoted to the optimization of the trajectory of a robotic system for aliquoting biosamples, consisting of serial and parallel manipulators. Optimization consists of two stages. At the first stage, optimization constraints associated with the workspace, taking into account the ranges of permissible values of the angles of the drive rotational joints, the link interference and singularities. The workspace in the space of input and output coordinates is represented as a partially ordered set of integers. At the second stage, restrictions are formed related to the objects that are in the workspace during the aliquoting process, such as the body of the robotic system, test tubes and racks. The condition for excluding collisions of the manipulator with other objects is provided by geometric decomposition of objects and exclusion of areas corresponding to external objects from the set describing the workspace of the manipulator. Optimization is performed in the space of input coordinates. The objective function is proportional to the duration of movement along the trajectory. The possibility of evolutionary algorithms application for solving this problem is analyzed. An assessment of their performance is given. Optimization and export of the resulting trajectory are implemented in software, which allows you to verify the optimization results on a virtual model. The simulation results are presented.

Keywords: optimization; aliquoting system; workspace

Citation: Rybak, L.; Malyshev, D.; Cherkasov, V. Virtual model-based trajectory optimization algorithm for aliquoting robotic system. *Eng. Proc.* **2022**, *3*, 0. https://doi.org/

Published: 21 September 2022

1. Introduction

When automating technological processes in a wide range of industries, trajectory planning tasks are very important. The boundaries of the workspace, singularities, and intersections of robot links can be considered as obstacles. Currently, there are various methods for trajectory planning. Some methods are based on the spatial decomposition into geometric shapes of various shapes [1,2]. Discrete search methods allows using heuristic estimates of the perspective of trajectories, speeding up the solution of trajectory planning problems[3]. An important family of motion planning methods consists of potential field methods, originally developed for mobile robot navigation and real-time obstacle avoidance [4]. Sampling methods allow us to solve problems of planning the trajectory of movement, with a high level of complexity: for spaces with a large number of obstacles and mechanisms with a significant number of degrees of freedom [5]. The Probabilistic Roadmap Method [6] is widely applied for solving path finding problems in both local and global settings. One of the ways to reduce the number of vertices in a graph is the method of constructing randomized route networks based on scopes [7]. There are also currently a number of efficient stochastic methods that can be applied to trajectory planning of manipulators [8,9].

The application of evolutionary algorithms makes it possible to solve optimization problems, including such as planning a trajectory with high performance indicators. In this regard, within the framework of this paper, an original approach is proposed based on the application of evolutionary algorithms to find the optimal trajectory inside the workspace of robots, taking into account singularities, intersections of links and restrictions on drive coordinates. The optimization problem is solved using the example of a delta robot, which can be applied for a wide range of tasks, including biometric aliquoting [10]. During this task, it becomes necessary to avoid obstacles such as test tubes and racks.

2. Setting an Optimization Problem

Delta robot (Figure 1b) included in the robotic system for biomaterial aliquoting (Figure 1a) has 3 degrees of freedom and includes three kinematic chains RUU. In each of the chains, the drive rotary joint A_i is used to connect to the base. Universal joints C_i are used to connect to the moving platform. Universal joints B_i are used for connecting two links between each other. The end-effector is the center P of the mobile platform.

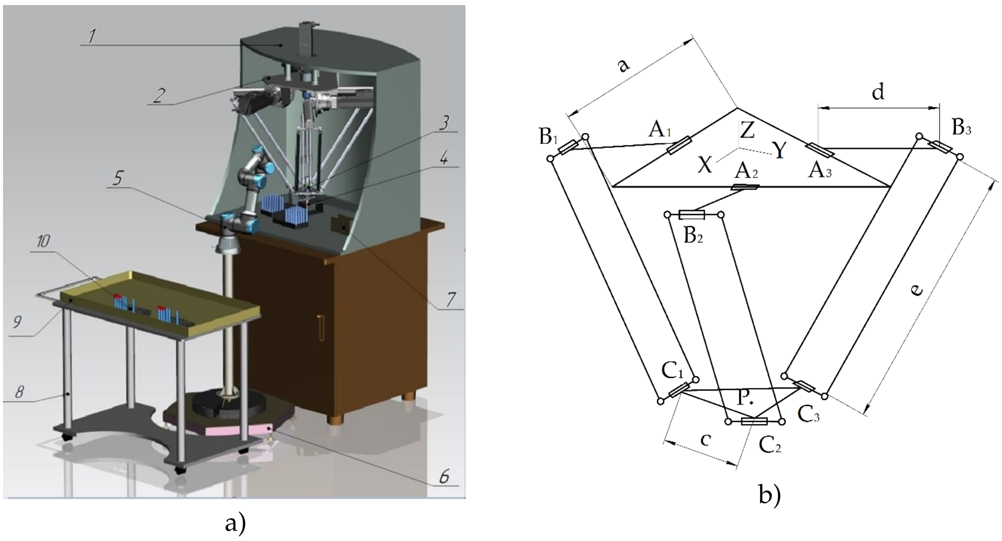

Figure 1. Robotic system: a) 3D model: 1—body, 2—DeLi manipulator, 3—dispensing head, 4—dispenser tip, 5—robot manipulator, 6—base of the robot manipulator, 7—workspace, 8—trolley, 9—tray for consumables, 10—rack with test tubes, b) delta-robot structure

The moving delta robot can move relatively freely along a certain arbitrary trajectory, taking into account the limitations determined by the workspace, taking into account singularities and intersections of robot links. The duration of robot movement should be minimized as much as possible. Since the duration of movement in time is determined by the duration of operation of robot drives required for the corresponding movement, it is advisable to optimize the trajectory in the space of input coordinates. So, for a delta robot, the input coordinates are the angles θ_i of rotation of the drive rotary joints A_i. An arbitrary trajectory can be represented as a set of movements (steps) in the space of $m = 3$ input coordinates. As a criterion function, it is proposed to use a function based on the Chebyshev metric, as well as the Euclidean metric, taken with some small weight coefficient ϵ [11]:

$$F = \sum_{i=1}^{n} \left(\max_{j \in \{1,2,\ldots,m\}} \left| \theta_{i,j} - \theta_{i-1,j} \right| + \varepsilon \sqrt{\sum_{j=1}^{m} \left(\theta_{i,j} - \theta_{i-1,j} \right)^2} \right) \to \min \tag{1}$$

Optimization should be carried out with restrictions on the size of the workspace. In the framework of previous works, the authors proposed to use the representation of the workspace in the form of a partially ordered set of integers A [12]. Therefore, checking the opt-in restriction consists of two steps.

2.1. the First Stage. Definition of the Set B of Trajectory Coordinates in the Space of Integers.

For this purpose, an algorithm based on a modification of the algorithm is developed Bresenham's algorithm [13], which assumes that the trajectory is represented as a polyline consisting of many segments. In this case, the coordinates must correspond to the covering set of the workspace, represented as a partially ordered set of integers, respectively, they must be obtained taking into account the accuracy of the approximation Δ_j and the displacement k_j along the j coordinate axes by the formula

$$x_i = \frac{\theta_{i,1} + k_1}{\Delta_1}, \quad y_i = \frac{\theta_{i,2} + k_2}{\Delta_2}, \quad z_i = \frac{\theta_{i,3} + k_2}{\Delta_2} \tag{2}$$

2.2. the Second Stage. Checking Whether the Resulting Set B a Belongs to the Workspace Set A.

Thus the optimization constraint condition has the form

$$B_i \subset A, i \in 1, .., n \tag{3}$$

where n is the number of segments that make up the trajectory.

Thus, the optimization problem looks like this.

- parameters: coordinates of intermediate points of the trajectory $x_i, y_i, z_i, i \in 1, .., (n - 1)$. For a delta robot, the coordinates are the rotation angles of the drive rotary joints, i.e. $[(x_i y_i z_i)]^T = [(\theta_{i,1}\theta_{i,2}\theta_{i,3})]^T$.

- parameter change range: overall dimensions of the workspace in the space of input coordinates $\theta_{(i,j)} \in [\theta_{jmin}; \theta_{jmax}]$. - criterion: the function F calculated by formula (1). - restriction: condition (3).

To increase the efficiency of optimization in the presence of obstacles, we transfer the optimization constraint to the criterion function

$$F' = F + \sum_{i=1}^{n} \left(\vartheta_i \left(p_1 \sqrt{\sum_{j=1}^{m} \left(\theta_{i,j} - \theta_{i-1,j}\right)^2} + p_2 \right) \right) \rightarrow \min \tag{4}$$

where p_1,p_2 are the penalty coefficient,and ϑ_i is the Heaviside function:

$$\vartheta_i = \begin{cases} 0, \text{if } B_i \subset A \\ 1 - \text{otherwise} \end{cases} \tag{5}$$

We use the Genetic algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO) to solve the optimization problem.

3. Numerical Results

The workspace of the delta robot is limited by the range of permissible rotation angles in the hinges, the area of sign constancy The Jacobian and the condition that there are no intersections of links. The problem of determining the workspace B_P for a delta robot in thespace of output coordinates is considered by the authors in [10]. Figure 2 shows the results for the following delta robot parameters: a = 600 mm, c = 100 mm, d = 350 mm, e = 800 mm, $\Delta_j = 4°$.

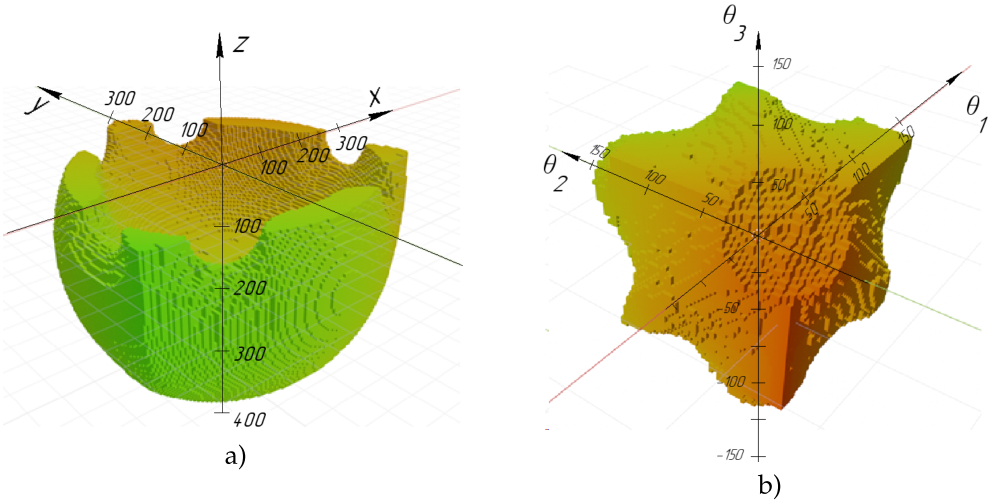

Figure 2. Workspace virtual model of the delta robot: a) in (x, y, z)coordinates, b) in coordinates $\theta_(i)$

An object was added as an obstacle with a parallelepiped shape (Figure 3a). The updated workspace virtual models are shown in Figure 3b, c.

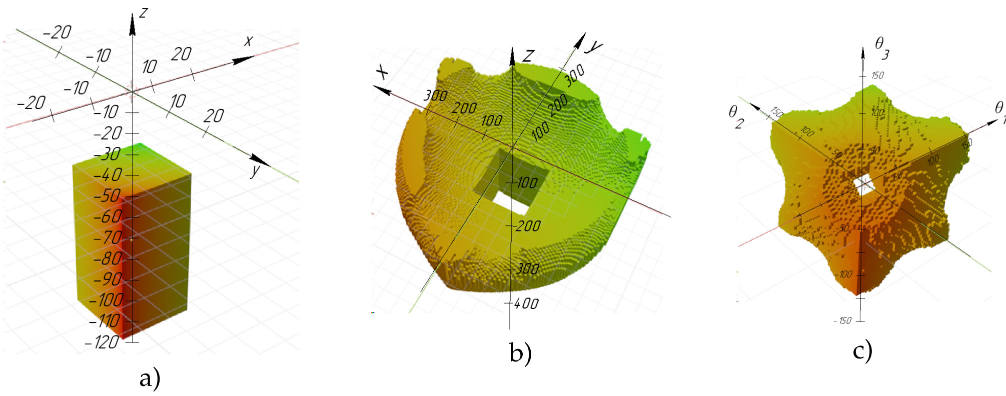

Figure 3. Additional boundaries, related to the overall dimensions of the obstacle: a) obstacle C; b) The set Bp given; c) B_P taking into account; c) Set B_θ given an obstacle

We perform trajectory optimization inside the workspace of a delta robot. A C++ software package has been developed for this purpose. Parallel computing is implemented using the OpenMP library. Visualization is performed by exporting an ordered set of integers describing the workspace in STL format and arrays of co-ordinates of trajectory points in JSON format, and then importing data in the Blender software package using developed Python scripts. Set the starting and ending points of the trajectory in the output coordinate space: $x_{p1} = 250$ mm, $y_{p1} = 250$ mm, $z_{p1} = -500$ mm, $x_{p2} = -270$ mm, $y_{p2} = -270$ mm, $z_{p2} = -450$ mm, and the number of vertices of the trajectory $n = 3$. Accordingly, the number of optimization parameters $p = 3n = 9$. The weight coefficient $\epsilon = 0,1$, the penalty coefficients $p_1 = 5$, $p_2 = 500$.

Parameters of the GA algorithm: the number of individuals in the initial population $H = 250$, the number of generations $W = 200$, the number of crosses at each iteration $S_{GA} = 125$, the number of possible values of each of the parameters $g = 2^{25}$, the probability of mutation $p_m = 70\%$.

Parameters of the GWO algorithm: $H = 250$, $W = 200$, number of new individuals at each iteration S_{GWO} = 1000.

Parameters of the PSO algorithm: $H = 250$, $W = 200$, number of groups G=2, values of free parameters α=0.7,β=1.4,γ=1.4.

Optimization for each of the tests was performed in four stages. At the first stage, the range of parameters was changed to the ranges corresponding to the overall dimensions of the workspace for each of the coordinates. The parameter ranges at each subsequent stage were reduced by a factor of 10^2. At the same time, the center of the ranges corresponded to the best result obtained at the previous stage. The optimization results are shown in Table 1. The GA algorithm showed the best average value of the criterion function.

Table 1. Results table, mm.

Trials	GA	GWO	PSO	Trials	GA	GWO	PSO
1	152,499	149,852	149,737	6	131,130	149,863	149,891
2	151,070	150,136	130,477	7	130,719	130,433	130,459
3	131,368	130,477	149,778	8	150,506	131,111	149,915
4	137,201	150,394	130,385	9	152,649	149,941	149,914
5	149,876	150,427	149,674	10	149,772	150,083	149,769
				Average. value	143,679	144,272	144,000

To justify the feasibility of using the criterial modified Chebyshev metric as a criterion function, we analyze the values of the trajectory length for various metrics and the criterion function for one of the tests. Table 3 shows the results of trajectory optimization for Test 3. The table shows that despite the fact that the trajectory obtained as a result of PSO optimization by the algorithm is 0.2% shorter in length than the trajectory obtained by the GA algorithm, however, the length in accordance with the Chebyshev metric and, accordingly, the positioning duration for the PSO trajectory is 14% longer. We can conclude that it is advisable to apply the Chebyshev metric when planning a trajectory.

Table 2. Trajectory optimization results for test 3, mm.

Trajectory according to test 3	GA	GWO	PSO
Path length	168,101	163,734	167,705
Chebyshev length (estimation of positioning duration)	114,558	114,104	133,008
Criterion function (α = 0,1)	131,368	130,477	149,778

Figure 9 shows the trajectories for Test 3 inside the workspace virtual model. As can be seen from the figure, the PSO algorithm found only a local minimum of the criterion function for avoiding the obstacle.

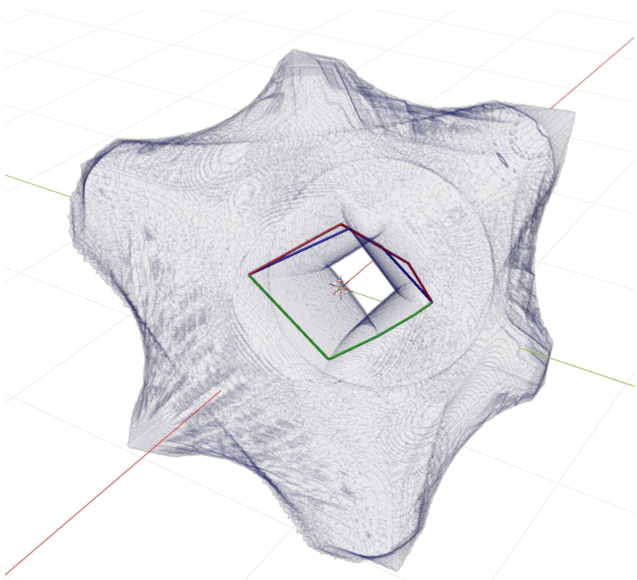

Figure 4. Trajectories inside the virtual workspace model: GA - red, GWO - blue, PSO - green.

4. Conclusion

The application of heuristic algorithms made it possible to solve the problem of planning a trajectory for a 3D workspace, represented as a partially ordered set of integers. It is shown that the planning of the trajectory in the space of input coordinates and the use of the Chebyshev metric as part of the criterion function makes it possible to reduce the duration of positioning from the initial to the final point of the trajectory. As part of future work, the choice of parameters of optimization algorithms will be performed to achieve the best convergence rates. Various modifications of heuristic algorithms, including hybrid ones, will be applied. A comparative analysis of the effectiveness of the developed methodology with existing methods of trajectory planning will be carried out.

Author Contributions: Conceptualization, L.R. and D.M.; methodology, D.M.; software, D.M.; validation, L.R., D.M. and V.C.; formal analysis, D.M.; investigation, D.M.; resources, D.M. and V.C.; data curation, D.M.; writing—original draft preparation, D.M.; writing—review and editing, L.R., D.M. and V.C.; visualization, D.M. and V.C.; supervision, L.R.; project administration, L.R.; funding acquisition, L.R. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the state assignment of Ministry of Science and Higher Education of the Russian Federation under Grant FZWN-2020-0017.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

GA	Genetic algorithm
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimization

References

1. LaValle, S.M.: Planning Algorithms. Cambridge University Press (2006).
2. Canny, J.F., Lin, M.C.: An opportunistic global path planner. Algorithmica **10**(2-4), 102–120 (1993).
3. Zeng, W., Church, R.L.: Finding shortest paths on real road networks: the case for A*. Int.J. Geogr. Inf. Sci. **23**(4), 531–543 (2009).
4. Khatib, O.: Real time obstacle avoidance for manipulators and mobile robots. International Journal of Robotics and Research **5**(1), 90–98 (1986).
5. Ericson, C.: Real-time Collision Detection. The Morgan Kaufmann Series in Interactive 3-D Technology. CRC Press (2004).
6. Ciaccia, P., Patella M., Rabitti, F., Zezula, P.: Indexing Metric Spaces with M-Tree. In: Proc. Atti del Quinto Convegno Nazionale SEBD, pp. 67–86 (1997).
7. Nissoux, C., Simeon, T., Laumond, J.-P.: Visibility based probabilistic roadmaps. In: 1999 IEEE/RSJ Int. Conf. Intell. Robot. Syst., pp. 1316–1321 (1999).
8. Gil Aparicio, A., Valls Miro, J.: An Efficient Stochastic Constrained Path Planner for Redundant Manipulators. Applied Sciences, **11**(22), 10636 (2021).
9. Bottin, M., Rosati, G.: Trajectory Optimization of a Redundant Serial Robot Using Cartesian via Points and Kinematic Decoupling. Robotics, **8**(4), 101 (2019).
10. Malyshev, D., Rybak, L., Carbone, G., Semenenko, T., Nozdracheva, A.: Optimal Design of a Parallel Manipulator for Aliquoting of Biomaterials Considering Workspace and Singularity Zones. Applied Sciences **12**(4) 2070 (2022).
11. Khalapyan, S., Rybak, L., Malyshev, D., Kuzmina, V.: Synthesis of Parallel Robots Optimal Motion Trajectory Planning Algorithms. IX International Conference on Optimization and Applications (OPTIMA 2018), pp. 311–324 (2018).

12. Rybak, L., Malyshev, D., Gaponenko, E.: Optimization Algorithm for Approximating the Solutions Set of Nonlinear Inequalities Systems in the Problem of Determining the Robot Workspace. Communications in Computer and Information Science **1340**, 27–37 (2020).
13. Rogers, D.: Procedural Elements for Computer Graphics. McGraw-Hill (1985).