Training Telemedicine Robots: A Path Planning Optimization Method for Educational and Medical Application

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Keywords: Educational Technology, Path Planning, Mereological Potential Field Algorithm, Educational Telemedicine Robot, Complex Labyrinth Map.

Abstract: In this paper, we present a Path Planning Optimization Method (PPOM) designed for educational telemedicine robots. Based on the mereological potential field algorithm, it integrates data preprocessing and optimization tools to enhance efficiency. Our method addresses navigation challenges in complex, tightly spaced medical environments while emphasizing its educational value. By incorporating data selection, cleaning, and transformation, PPOM enables efficient path planning in maze-like layouts with long, narrow corridors, mimicking real-world hospital wards and patients' homes. This equips telemedicine robots to navigate local traps and tight spaces, providing a robust framework for training students and professionals in robot navigation and decision-making. Simulation results confirm PPOM's high performance in complex environments. The algorithm ensures precise navigation and effective obstacle avoidance, making it ideal for telemedicine applications. Unlike classical methods that struggle with blocked nodes, PPOM selects sectors, minimizing obstructions and improving computational efficiency. This enhances route passability, optimization, and reliability in dynamic environments.

1 INTRODUCTION

With the changing world, the expectations and skills of computer science students in using future technologies, such as telemedicine and robotics, are evolving. To enhance student learning in the UWM lab, we built obstacle models simulating hospital room conditions and tested robot performance in these settings. During the experiments, we identified specific obstacle configurations (beds, sanitation, medical devices) that introduced a new challenge in path planning: positioning obstacles in a way that creates local traps for the robot. Analyzing these critical cases using two mathematical methods led to the development of a path planning algorithm that effectively resolves this issue. As part of an educational activity, students implemented the algorithm model into a robot and conducted successful physical simulations. The algorithm is easily adaptable for new educational robots and has broader applications in indoor path planning for small robots. The successful implementation of this algorithm has inspired students to engage more deeply in scientific research, leading some to join the robotics research club. The project's execution marks both a scientific and educational success.

It is worth mentioning that the use of teamwork and active learning methods in this project contributed to the development of students' competencies in terms of cooperation and responsibility for joint actions. According to the results of the research (Planas-Lladó et al., 2021), self-assessment and peer assessment in the context of teamwork in higher education can significantly affect the development of students' interpersonal and professional competencies, which was also reflected in our project implementation. In addition, the use of collaborative learning techniques, such as group work and sharing knowledge and responsibility for the implementation of tasks, is in line with the assumptions presented in the publication (Taxirovna, 2024), (Falcione et al., 2019). Interactive student engagement improves cognitive abilities in the learning process and affects the overall educational development of young people. The study (Othman and Zaın, 2015) assessed the effect of online collaboration on the cognitive abilities of programming students, especially in the area of logical thinking and problem-solving skills. The results showed that after

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Samojluk, A. and Szpakowska, A.
Training Telemedicine Robots: A Path Planning Optimization Method for Educational and Medical Application.
DOI: 10.5220/0013481400003932

In *Proceedings of the 17th International Conference on Computer Supported Education (CSEDU 2025) - Volume 1*, pages 147-157
ISBN: 978-989-758-746-7; ISSN: 2184-5026

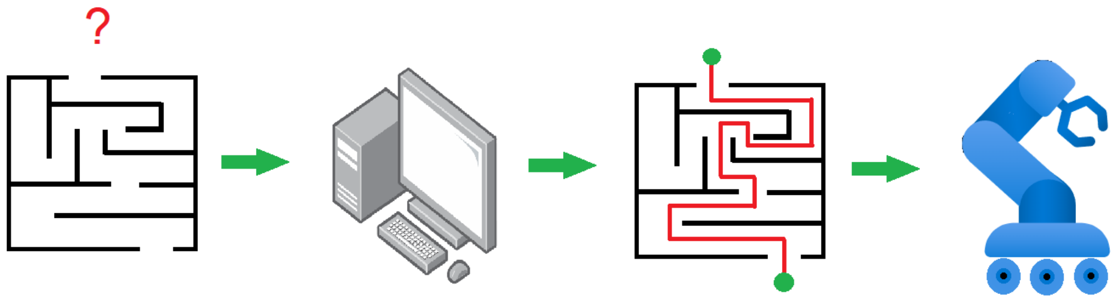


Figure 1: Graphic representation of system operation - path planning in a labyrinth.

the interactive session, the number of students with a high level of logical thinking increased from 30% to 51.7%, which is an improvement of 21.7%. Additionally, when analyzing the effectiveness of solving programming tasks, it was shown that 53.3% (8 out of 15 groups) were able to solve more complex problems requiring analysis. These results indicate that interactive teaching methods based on online collaboration can significantly support the development of students' cognitive abilities in the area of programming. This theory is also supported by the study (Nurdin and Setiawan, 2016), in which interactive technologies increased students' cognitive abilities. These methods not only increase student engagement but also promote the development of critical thinking and the ability to solve problems independently. Thanks to this project, it was possible to achieve not only educational goals but also to awaken in students a passion for further development in robotics and automation.

The main idea of this study on optimizing the path planning process for telemedical robots came from the key methodology developed by Polkowski and Skowron (Polkowski and Skowron, 1996). The results of this work, which utilized mereological potential fields, were applied in a subsequent publication (Polkowski and Ośmiałowski, 2008), and (Ośmiałowski and Polkowski, 2010). The motivation for researching using and improvement of path planning algorithms came from the implementation of another telemedical project. The mentioned project focuses on creating a voice telemedical system that enables remote and automated medical interviews with patients, commissioned by the National Centre for Research and Development in Poland. During the project implementation, it was observed that the system could more effectively fulfill it is assumptions in a hospital context if it were possible for medical interviews could be conducted directly with patients. This led to the idea of a robot that could monitor patients in hospital wards and, if necessary, approach the bed of a patient to conduct a conversation. Analysis revealed that the layout of beds in the hospital, and it is equipment, create a kind of labyrinth from the perspective of the robots, making it difficult to quickly reach the destination. To the robot efficiently reach the designated location without disrupting the staff of the medical, taking into account the correct side of the bed of the patient, it must be able to rapidly learn the environment and dynamically plan paths to designated points. The research problem is associated with the need to endow the robot with 'human spatial intuition' to enable planning the trip to the chosen location (the problem of route passability). Thus, the demand for quick and safe access to the telemedical robot became the key motivation for conducting research in this field.

This study aims to enhance the path planning proposed by Szpakowska et al. in 2023 (Szpakowska et al., 2023) which utilizes a mereological potential field algorithm by applying an additional decision-making system. The mentioned extension focuses on reducing the number of generated potential fields by analyzing and concerning defined sectors that represent the split part of a map. Additionally, there is an effort to modify an existing path planning algorithm by adding new functions like checking if two chosen potential fields have not been connected by a line crossing an obstacle field. Furthermore, this paper applies increased automation to the path-planning algorithm. The process begins by generating the mereological potential field, and after that filtering the list of potential fields by removing unnecessary data. The action of reducing data starts from map analysis. A decision-making system checks if between two close sectors exists any vertical or horizontal connection, if so the system treats sectors as passable. The number of potential sector combinations could be substantial; hence, one of the deciding factors is selecting the combination with the fewest sectors. The algorithm analyzes sectors until it gets the list of connected sectors from the determined start to the goal. The returned sector list contains all potential fields that fall within them. The truncated list of potential fields in which any possible path certainly exists is passed to the path search algorithm, thanks to which we have got the accurate path. The proposed solution solves the problem of complicated maps containing many obstacles. Examples of such an environment are hospital wards or homes of the patients. The next sections will show the effectiveness of the proposed algorithm. The mentioned research takes into account labyrinthine cases and environments characterized by long narrow corridors similar to different types of medical environments. To get better results we applied a path-planning algorithm, which gave us a clear, unambiguous route. Such operations provided the optimal path for the telemedical robot. The next part of the study will explore further developing a decision-making system using principles of rough sets.

1.1 Educational Applications

Interactive Learning Tools. The proposed algorithm serves as a good platform for teaching robotics, allowing students to gain practical understanding of path-planning algorithms in realistic environments.

Development of Analytical Thinking. Students learn to analyze problems and design solutions, which strengthens their ability to think logically and strategically in situations that require quick decision-making.

Simulations in Education. The use of physical simulations in laboratories enables students to gain experience in environments resembling real-world scenarios, enhancing their practical skills.

Interdisciplinary Integration. The project encourages collaboration among students from different fields, such as computer science, mechanics, and medicine, promoting an interdisciplinary approach to learning and problem-solving.

Supporting Innovation. The algorithm inspires students to experiment with their own modifications and develop new features, supporting creativity and innovative thinking.

1.2 Research Applications

Algorithm Optimization. The PPOM method enables further refinement of path-planning algorithms, increasing their efficiency in complex environments.

Applications in Medicine. The algorithm is specifically designed to meet the unique needs of medical environments, such as narrow corridors and crowded spaces in hospitals.

Solutions for Dynamic Environments. The algorithm can be adapted to rapidly changing conditions, making it an ideal tool for research in dynamic and adaptive robotics.

Collaboration in Multi-Robot Systems. The algorithm supports synchronization and coordination among multiple robots, opening new opportunities for research in multi-agent systems.

Foundation for Further Research. The research findings can serve as a basis for developing new methods in robotics, mereology theory, and decision-making algorithms, supporting the advancement of emerging technologies.

2 ROUGH SET THEORY AND ROUGH MEREOLOGY

Rough set theory (Pawlak, 1992) employs lower and upper approximations to facilitate the classification of ambiguous data, providing a means to navigate uncertainty without the need for additional external parameters. Rough sets have found extensive applications in various fields, notably in data analysis, where they aid in uncovering hidden patterns and relationships within imprecise datasets (Komorowski et al., 1999). Rough mereology (Polkowski and Skowron, 1996), a subsequent development in this domain, extends the foundational principles of rough sets to encompass the concept of 'part to a degree'. Developed to address the limitations in traditional mereology, rough mereology allows for a more flexible understanding of part-whole relationships in contexts where precision is unattainable. The reasoning based on rough mereology introduces the concept of rough inclusion, denoted as $\mu(x,y,r)$. This relation posits that x is a part of y to a degree of at least r. Given our focus on spatial objects, the rough inclusion is expressed as $\mu(X,Y,r)$ if and only if $\frac{|X \cap Y|}{X} >= r$, where X and Y represent n-dimensional solids and $|X|$ signifies the n-volume of X. The synergy between these two theories provides a comprehensive framework for the analysis of non-binary, uncertain data structures. The ongoing evolution of rough set theory and rough mereology continues to contribute significantly to advancements in data science, offering new perspectives and methodologies for dealing with the complexities of modern data.

3 BASIC POTENTIAL FIELDS ALGORITHM AND SOME UNIQUE ARRANGEMENT OF OBSTACLES

We would like to begin by discussing the fundamental mechanisms of the potential fields algorithm (Polkowski and Skowron, 1996), it is advantages, as well as the critical situations that can arise when using this algorithm. The concept of the potential fields algorithm was introduced in works (Polkowski and Ośmiałowski, 2008) and (Ośmiałowski and Polkowski, 2010), (Osmialowski, 2011) in the last paper special variant named the Square Fill Algorithm. The mentioned method already was modified and later presented in Polkowski (Polkowski et al., 2018), Zmudzinski and Artiemjew (Zmudzinski and Artiemjew, 2017), Gnys (Gnyś, 2017) and Szpakowska, Artiemjew and Cybowski (Szpakowska et al., 2023) on which this paper based on.

3.1 Intersection Condition

The algorithm performs admirably in scenarios where a limited number of obstacles are present. In cases where the map offers ample open space for navigation, seamless operation is observed. However, challenges arise when applying the algorithm to maps resembling mazes, characterized by a proliferation of obstacles. In such instances, the algorithm occasionally neglects crucial obstacle-avoidance rules, leading to lapses in connecting the current field with the most strategically advantageous option in the given step, which is forbidden - see fig.2.

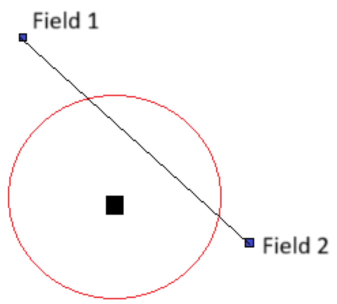


Figure 2: Unexpected intersection between current potential field and 'the most attractive field', which should not appear.

To solve this unexpected action the intersection checking was applied. A few steps were added to the existing patch search algorithm (Szpakowska et al., 2023) to improve the performance of the program.

Initially, each iteration of the path planning function involves the creation of a linear function between the current and next potential fields. Subsequently, an obstacle field was established through the creation of circular zones. The circle's center coincided with the obstacle's center, and the radius was determined by a parameter specified in the existing obstacle-checking function.

The subsequent step focuses on verifying whether the linear path intersects with any of the circular obstacles. This was achieved by generating a series of points along the path. The outcome, denoted as True or False, determines the feasibility of establishing a viable path between the two evaluated points, based on the intersection or absence thereof with the obstacle circles.

3.2 Unique Arrangement of Obstacles

The Mereological Potential Fields algorithm systematically extends from the goal towards the map borders, intelligently navigating to avoid obstacles. An advantageous feature of this algorithm lies in it is capacity to comprehensively explore the entire map. The user can effortlessly discern a goal location based solely on the spatial arrangement, leveraging the accumulation of potential fields.

Given this interdependence, it becomes evident that the crucial factor is the strategic placement of potential fields, influencing not only the goal position but also delineating the locations of obstacles. Despite the widespread presence of potential fields throughout the whole map, their deployment may appear excessive in scenarios where a direct, optimal path is sufficient.

Conversely, the abundance of potential fields presents numerous opportunities. In intricate scenarios characterized by a substantial number of obstacles, the increased density of generated fields proves invaluable for identifying alternative routes. Regrettably, challenges arise in cases where the fundamental path-planning algorithm struggles to cope, particularly in more intricate scenarios.

Figure 3 shows one of the examples of critical cases when the path was not found. The algorithm finishes work with the result of getting stuck in one place, without any possibility to find the goal.

Map Legend:

- One-color painted square represents the start point,
- Extreme markers determine map borders,
- Circles with squares describe obstacles and those fields,
- Goal is represented by a marker

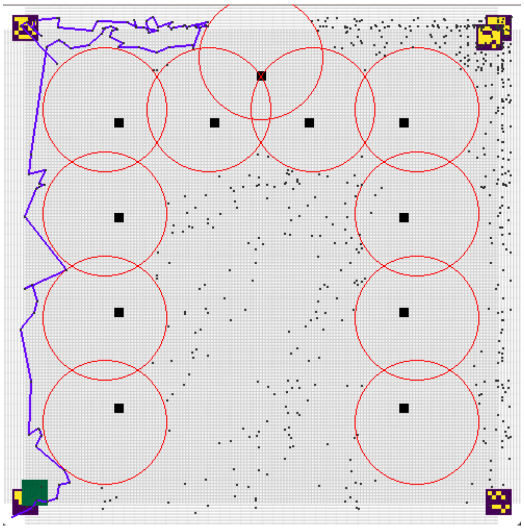


Figure 3: Critical case with determined goal position on point (490,490) - down left corner, and start point in (10,10) - top right corner.

To solve the problem of complex cases we propose the Route selection system (read Section 6)

4 ADDRESSING THE CHALLENGE OF UNIQUE ARRANGEMENT OF OBSTACLES

The basic potential fields algorithm generated a series of exceptions that prevented finding a path to the destination. After analyzing cases where such a situation occurred (see fig. 3), it was observed that they were associated with directing the path into a closed area (without passage), often characterized by a narrow entrance. Consequently, the algorithm in it is current form was unable to find a return path. To avoid this scenario, an improvement was introduced, consisting of a probabilistic determination of whether the designated path has a realistic chance of reaching the destination. This approach involves a general examination of the map and identification of areas that could be critical for planning a detailed route. Subsequently, the basic algorithm is activated and steered towards areas that have undergone preliminary examination and, problematically, present a higher likelihood of passage.

5 NEW CONCEPTION AND DEVELOPMENT OF MEREOLOGICAL POTENTIAL FIELD ALGORITHM

In this section, the mechanics of the algorithm PPOM are presented, along with a sequential description of the actions that should be performed in a specified order:

1. Obstacles are introduced onto the map, in this case in the form of circles. Points overlapping with obstacles are removed.
2. The points (potential fields) are generated on a 2D map with coordinates (X,Y) concerning the rules of generating mereological potential fields (Polkowski and Ośmiałowski, 2008),(Osmialowski, 2011), using the square fill algorithm (see references (Osmialowski, 2011), (Szpakowska et al., 2023)).
3. The map is divided into sectors, with the minimum division being 2x2 (4 sectors). The computational complexity increases with a higher division of the map into sectors. A greater division into sectors is recommended for maps with many small, interconnected obstacles. Here, we use a division into 3x3 (9 sectors), as per the following scheme: *We start numbering from the top left corner, numbering to the right.*
   An example of how the map is divided into sectors is illustrated in Fig. 4.
4. For the sake of computation organization, sectors are numbered starting from the top left corner, and then from left to right (fig. 4).
5. Every sector is subjected to a separate drivability analysis. The algorithm checks simplified paths in each sector for four directions: vertical, horizontal, diagonal left, and diagonal right (see fig. 4). Passable paths are marked in green, and impassable ones in red (fig. 4). In total, 12 paths are checked for each sector, and the overall drivability of a sector is calculated as the ratio of passable paths to the number of paths tested.
6. Building potential paths in a sector perspective. We determine all possible paths through sectors, starting from the defined starting sector and ending at the defined ending sector. The path can only move forward, changing direction vertically, horizontally, or diagonally, without repeating sectors.
7. Analyzing possible paths. Each potential path is analyzed for drivability and components such as the number of obstacles, points, and whether the

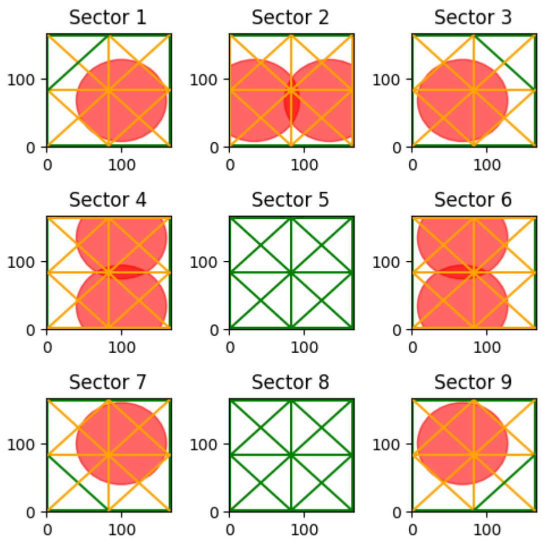


Figure 4: Testing sector passability.

path has at least one passable route in each sector. The probability of passage through the path is calculated.

8. Selection of passable routes. We eliminate all paths from the list that contain at least one sector deemed impassable.
9. Classification of routes, data discretization, and selection of the best route using the designed classifier. We create a table of passable routes and then apply discretization (according to a set of rules) to select the best route according to the decision matrix.
10. Extraction of route points. From the selected best route, we record the points belonging to the route sectors into a new array.
11. Implementation of the potential field algorithm. We overlay the filtered map with a table of points to maximize the chances of passage.
12. Generating the optimal route using the potential field algorithm, maintaining flexibility within safe sectors.
13. Apply the path smoothing algorithm by taking into account 3 points in order.

In the next section, we will discuss the main attributes that make up the path vector. The elements discussed and the way they are classified is crucial for the proper functioning of the algorithm.

6 PATH SELECTION SYSTEM BASED

This section will discuss the decision-making mechanisms used in the presented algorithm.

6.1 Choosing Proper Sectors for Finding the Optimal Path

A decision-making system was employed to select the optimal path among the vectors of paths containing various attributes. This approach allowed for the development of an efficient decision-making mechanism in situations where multiple paths meet the basic drivability condition. The primary condition for path drivability is the presence of probabilistic conditions allowing for passage between obstacles. If a path in even one of the sectors on the planned route contains a set of obstacles that prevent direct passage, it is considered impassable (see fig. 4). When a path is deemed passable, the probability of a successful passage is determined. The higher the probability, the better the quality assessment of the path. The chance of passability is one of the key attributes used in assessing the quality of the path.

The decision-making mechanism used in the algorithm employs Hamming distances (Waggener and Waggener, 1995), (Hamming, 1950). Since the input data metrics in vectors are numerical, there is a need to discretize them. The data discretization process was conducted according to specially defined formulas and rules for the algorithm, which establish thresholds for determining binary values.

6.2 Data Preparation

In the current subsection, we will focus on the steps responsible for data preparation and the rules applied to prepare data for computation through discretization.

Example data preparation (path vector discretization):

$$[1, 0.5, 5, 438, 5] \rightarrow [\text{Yes, High, Low, High, Low}].$$

The attribute names of the above vector (according to the order of elements in the vector) are as follows:

- **road_pass** → value from 0 to 1, discrete value: No or Yes,
- **pass_probability** → value from 0 to 1, where 1 is 100% pass probability, discrete value: Low or High,

- **path_length** → counted in the number of sectors, discrete value: Low or High,
- **points_on_path** → number of mereological points on the path, discrete value: Low or High,
- **obstacles_on_path** → number of obstacles on the path, discrete value: Low or High.

Next, we will discuss step by step how to discretize any vector.

6.2.1 Data Discretization

The data discretization process is a key element of the presented algorithm and plays a crucial role in preparing data. Given the application of Hamming measures in the decision-making model, it is essential to process the data in such a way that numerical attributes are converted into binary values. Special formulas and rules have been developed for each attribute that requires discretization. These rules define thresholds that allow the transformation of numerical attributes into binary decision values. Below, the applied formulas are described in detail, and specific threshold values are indicated, which are necessary for the algorithm to perform calculations correctly. These formulas have been adapted to the specifics of the data and the nature of the problem the algorithm is intended to solve, thereby ensuring it is efficient and effective.

Discretization of the Number of Points on the Path T_ρ

The following formula $T_\rho = \frac{\mathrm{p}}{\mathrm{n}} \times \mathrm{l}$ is used to calculate the threshold indicator (average) expected number of points that should be found on a path of a given length l. Where T_ρ is a Threshold Number Of Points, p represents the total number of points on the map, n is a number of sectors calculated as rows × cols and l is the length of the path.

For the attribute of the examined path to be classified as 'yes', the actual number of potential field points on the examined path must be greater than the value T_ρ. If the number of points is less than the value T_ρ, the attribute is marked as 'no'.

In the next step of the discretization process, we will perform discretization of the path length.

Discretization of the Path Length T_λ

Determining whether a path is short (yes) or long (no) is an essential attribute for making a good choice of the optimal route. The optimal length of the path is related to the number of sectors on the map. It is assumed that paths no longer than the route along the outer edges are considered quick to traverse (yes). The threshold value of the path length is determined by the following formula $T_\lambda = \mathrm{r} + \mathrm{c}$. Where T_λ is the Threshold Path Length, r is the number of rows in the grid, and c is the number of columns in the grid.

Remark. It should be noted that the exact threshold value of the path length is $r + c - 1$; however, to provide a larger buffer for routes and to avoid a situation where the path length is too dominant a factor, it is better to use a threshold length equal to $r + c$.

Discretization of the Number of Obstacles on the Path T_θ

The threshold indicator $T_\theta = \frac{\mathrm{o}}{\mathrm{n}} \times \mathrm{l}$, similar to the previously discussed threshold indicator of points T_ρ, is used to calculate the threshold (average) expected number of obstacles that should be present on a path of a given length l.

Where T_θ is the Threshold Number Of Obstacles, o is the total number of obstacles, n is computed as rows × cols and l refers to the length of the path. For the attribute of the examined route to be classified as 'yes', the actual number of obstacles on the examined path must be less than the value T_θ. If the number of obstacles is greater than the value T_θ, the attribute is marked as 'no'.

Next, we have to discuss the last, and one of the most important indicators of the route, which defines the probability of the passage of the route.

Discretization the Probability of Passage T_α

The discretization of the probability of passage attribute T_α was determined experimentally. The optimal threshold coefficient was set at $T_\alpha = 0.35$. This value is related to the probability of passage and can be interpreted as total freedom of movement on a passable route. An actual value above 0.35 means that more than 35% of all possible movements in sectors (vertical, horizontal, and diagonal movements) of the route are possible. The higher the indicator value, the better the situation, hence if the attribute takes on a value greater than 0.35, we consider it as 'yes'; values below this threshold are considered as 'no'.

6.3 Route Vector Similarity Comparison

After performing the path discretization, we proceed to check the degree of membership of the discretized path vector concerning the learning matrix α (see tab. 1). For this purpose, we use the classifier, designed to make decisions in the selection of the optimal path. The classifier uses Hamming distances to calculate the similarity between sets of attributes. Then, it performs upper and lower approximation calculations and determines boundary values. Using the determined approximations and boundary values, a classification of the input attribute sets (path vectors) is performed. Classification consists of finding the attribute set in the α matrix that is most similar based on Hamming distances. For new attribute sets entered for classification, a decision from the α learning matrix is assigned. The vector that shows the highest degree of similarity to the 'yes' decision is selected for final use. When two vectors or more have the same degree of similarity to the 'yes' decision, the lowest value of the degree of similarity to the 'no' decision decides the selection.

6.4 Using Learning Matrix α

The decision-making system utilizes a defined decision matrix α. This matrix contains rules that determine the quality level of each path. The quality level of a path is defined as the degree of membership of the path vector to the most optimal solution (vector) specified in the matrix α (see tab. 1). Decision vectors marked as 'yes' are considered the most desirable in evaluating the path quality. The more a path attribute vector resembles the optimal vector defined in matrix α, the better it is considered in terms of quality compared to other less similar vectors. Conversely, vectors in matrix α marked as 'no' are regarded as the least desirable.

In the table below, the row with bold attributes presents a sample decision for the path vector solved using the PPOM method (see fig. 5):

[7, [7, 8, 9, 6, 3], 1, 0.48333333333333333, 5, 449, 5]

Next, the vector needs to be prepared for the decision-making process. To do this, we omit the first three attributes that are not required in the decision-making process but are used to store information about the path (Path ID, Path sectors, and Passability). To make a decision, the Passability attribute must be 1 (meaning that the path has a probabilistic chance of being passable). The following attributes remain pass_probability, path_length, points_on_path, obstacles_on_path. For the presented example, we create a shortened vector:

[0.48333333333333333, 5, 449, 5]

Now we discretize it according to the rules described in the previous chapter and obtain the vector:

['High', 'Low', 'High', 'Low']

Next, we search the decision table α for the decision most similar to the analyzed vector.

Table 1: Learning Matrix α.

Pass probability	Path length	Points on path	Obstacles on path	Decision
High	**Low**	**High**	**Low**	yes
High	Low	Low	Low	yes
High	Low	Low	High	yes
High	Low	High	High	yes
High	Low	High	High	no
Low	High	Low	Low	no
Low	High	High	High	no
Low	High	Low	High	no

The learning matrix α was developed based on experiments and achieved the best results in the decision-making process of choosing the optimal route.

In the next section, we will analyze several cases of maps with obstacles that posed challenges for the basic version of the algorithm. We will then compare these cases with solutions generated by the improved version of the potential fields algorithm.

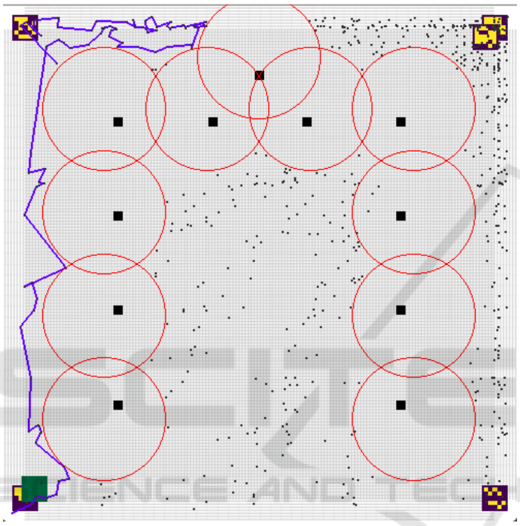
7 ANALYSIS OF RESULTS

The results of the presented algorithm have been demonstrated through the comparison of several repeatable critical scenarios, simulating situations that telemedicine robots may encounter in real-world environments, such as hospitals or patients' homes. These scenarios are designed not only to evaluate the algorithm's efficiency but also to serve as educational case studies for training purposes. The basic potential field algorithm, known for its limitations in complex environments, is contrasted with the improved version, with the comparison structured as follows: the basic algorithm is presented on the left side (critical solution), and the improved algorithm – on the right side.

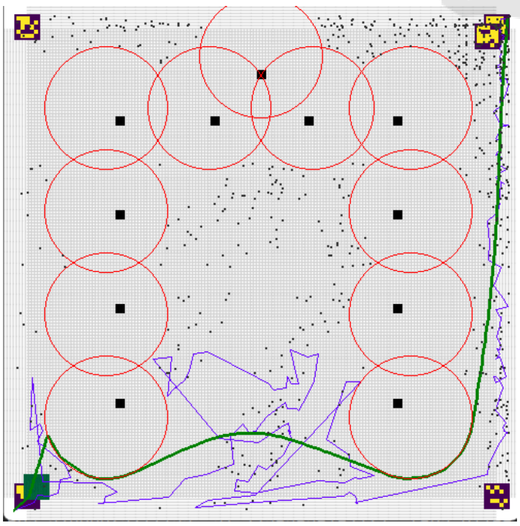
As observed in the figures below (fig. 5), the critical scenarios involve situations such as navigating through 'narrow passages' or areas densely populated with obstacles. These are particularly challenging due to the limited number of potential field points in such spaces. When the basic algorithm encounters an impassable obstacle, it often fails to recover by turning back or finding an alternative path, leading to complete route blockage.

In contrast, the improved algorithm employing preprocesses the environment map to identify and exclude areas with a high likelihood of obstruction. This preprocessing step provides an opportunity for learners to understand how predictive analysis and preprocessing can significantly enhance the performance of robotic systems. By directing the robot through passable sectors identified during preprocessing, the improved algorithm ensures successful navigation through previously impassable scenarios.

These findings not only highlight the practical advantages of the enhanced method but also demonstrate its pedagogical value in training students and professionals. The ability to visualize and analyze these critical cases fosters a deeper understanding of robotic navigation challenges and equips learners with the skills needed to address similar issues in diverse environments. By simulating such scenarios, the framework provides a unique opportunity to combine theoretical knowledge with hands-on problem-solving experience.



(a) Case 1: critical solution



(b) Case 1: PPOM solution

Figure 5: Case 1: critical problem and PPOM solution.

In a further 9 case studies performed on maps with a different configuration of obstacles and points, the algorithm solved the passability problem and planned the path correctly.

8 ALGORITHM COMPLEXITY

Path Planning Optimization Method (PPOM) is an advanced combination of two methodologies, integrating heuristic approaches for efficient path planning in obstacle environments. This algorithm, through its complex structure of operation, aims to overcome the limitations of classical heuristic methods, which in the case of an unfavorable obstacle configuration can fall into the so-called ”local traps”, while requiring a significant number of computations to find the optimal path to the goal. In response to these challenges, PPOM implements a two-step approach: the first module of the algorithm selects key sectors of space that maximize the probability of finding the optimal path, while the second module uses greedy heuristic algorithms to choose the best local solution in a previously defined space.

The first component of the algorithm acts as a high-level selector, selecting the main sectors of space based on the probability of minimizing interactions with obstacles that could prevent further route search. The number of possible paths in this part of the algorithm is constant and equal to C = 235 (for dividing the map into a 3x3 grid of sectors). This means that the computational complexity of this phase is O(1), which implies a constant computational complexity, independent of the size of the input data.

The second component of the algorithm is responsible for precise route determination using potential fields that model the map space. The complexity of this part of the algorithm is determined by the number of points in the potential field space. The number of steps in this stage is proportional to the number of points on the map, which leads to a linear complexity of O(N), where N is the number of potential field points.

Considering both stages of the algorithm's operation, its overall computational complexity is O(C * N), which indicates a linear dependence on the number of points in the potential space.

It should be emphasized that the given complexity refers to cases with the highest level of complexity. In typical conditions, the computational complexity of the algorithm is much more efficient, which is beneficial in the context of a wide range of applications. Unlike classical path finding algorithms, which do not take into account the aspect of route passability

Table 2: Comparison of PPOM Algorithm with Other Pathfinding Algorithms.

Algorithm	**Computational Complexity**	**Complexity Type**	**Is PPOM faster?**	**Paper Reference**
PPOM	$O(C \cdot N)$	Linear	-	-
A*	$O(b^d)$	Exponential	Yes	(Hart et al., 1968)
Dijkstra	$O(E \cdot \log V + E + V \cdot \log V)$	Polynomial	Yes	(Dijkstra, 1959)
BFS	$O(\|V\| + \|E\|)$	Linear	No	(Moore, 1959)
DFS	$O(\|V\| + \|E\|)$	Linear	No	(Tarjan, 1972)
Bellman-Ford	$O(\|V\| \cdot \|E\|)$	Polynomial	Yes	(Bellman, 1958)
Johnson's Algorithm	$O(\|V\|^2 \log \|V\| + \|V\|\|E\|)$	Polynomial	Yes	(Johnson, 1977)
Floyd-Warshall	$O(\|V\|^3)$	Polynomial	Yes	(Floyd, 1962)
IDA*	$O(b^d)$	Exponential	Yes	(Korf, 1985)

in the face of obstacles, PPOM effectively copes with this issue. In traditional algorithms, graphs containing obstacles generate decision nodes that can lead to situations in which it is impossible to continue the path search. PPOM eliminates this risk through intelligent selection of sectors, minimizing the probability of problematic decision nodes, which significantly increases the efficiency and computational optimization in environments with obstacles.

9 CONCLUSIONS

As a result of this research, a new algorithm has been developed to enhance the performance of basic path planning methods in environments with numerous obstacles using potential fields. This improved algorithm reduces the likelihood of paths leading into 'traps,' which are typically closed areas with narrow entrances. It incorporates a decision-making system allowing for the selection of the most likely successful path for a robot. Furthermore, it minimizes unnecessary wandering during path planning, which is particularly beneficial for large maps containing labyrinth-like structures with dead ends.

The effectiveness of the improved algorithm was assessed using 10 different critical scenarios, representing typical challenges of navigating 'narrow passages' that lead to impassable routes. In 8 out of the 10 cases, the algorithm successfully identified a viable path. The tests utilized a division of the map into a 3x3 grid (3 columns and 3 rows), which proved to be an optimal configuration relative to the obstacle sizes used in the experiments. For environments with significantly smaller obstacles, a larger grid division, such as 4x4, is suggested. It is also recommended that the division of the map be as symmetrical as possible, with sector sizes close to square shapes to ensure uniform coverage.

However, increasing the map division size raises the computational complexity, as the number of potential paths grows significantly. It is therefore advised to determine the optimal grid size experimentally, balancing computational efficiency with navigational precision.

This study achieved its objective by demonstrating the effectiveness of the proposed algorithms in addressing complex navigational challenges. The results confirm that the algorithm excels in environments with intricate layouts, such as hospital wards or patient residences resembling mazes. The generated paths ensure precise navigation while effectively avoiding obstacles, making the system well-suited for telemedicine applications.

Future applications of the PPOM algorithm include its integration into telemedical robots for practical use in real-world settings. These robots will navigate hospital spaces while considering the physical layout of obstacles, such as medical equipment in rooms. Furthermore, they will be equipped to actively and directly interact with patients, providing an educational tool for training operators and students in navigating complex environments with robotic systems.

Additionally, we plan to further improve the algorithm and test it in the task of avoiding obstacles in the form of rock mazes, simulating the movement of a ground drone in desert conditions on Mars.

ACKNOWLEDGEMENTS

This work has been supported by a grant from the Ministry of Science and Higher Education of the Republic of Poland under project number 23.610.007-110 and a grant from the National Centre for Research and Development in Poland, grant number: POIR.01.01.01-00-0587/21 Development of telemedical software for conducting automated subjective patient examination and enabling preliminary medical diagnosis based on AI.

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