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HYBRID PATH PLANNING METHOD FOR UNMANNED GROUND VEHICLES SWARM IN DYNAMIC ENVIRONMENTS

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Unmanned ground vehicles (UGVs) have significant potential across various applications. These include automation of the agricultural tasks, inspection and maintenance within construction and industrial sectors, automation of complex assembly processes and infrastructure repairs, explosives disposal, automation of logistical operations, search-and-rescue missions, and expeditions to hard-to-reach or hazardous areas. However, a key challenge limiting their widespread deployment is autonomous navigation, which remains a significant problem due to dynamic environments characterized by constantly changing obstacle configurations, unpredictable scenarios, and the need for rapid real-time decision-making to ensure safe and stable movement.

The object of this paper is a hybrid path planning for the autonomous navigation of unmanned ground vehicles swarm within a simulated environment. The research aims to develop autonomous navigation method for the unmanned ground vehicles swarm by employing a hybrid approach designed to enhance the efficiency of obstacle avoidance and improve the adaptability to dynamic environments.

To achieve this goal, a novel autonomous swarm navigation method based on a hybrid approach is proposed. This approach differs from existing solutions by employing the A* path planning algorithm with incorporated traversal costs on the map for global-level navigation and the artificial potential field (APF) algorithm, that supports linear and V-shaped formations for local-level navigation.

The research findings indicate that the proposed method allows the swarm to perform optimal path planning, considering traversal costs, and effectively avoid local minimum problems that are inherent to the artificial potential field method. The successful performance of the method within the simulated environment demonstrates its potential for future validation in real-world scenarios and practical applications involving swarms of unmanned ground vehicles operating in challenging environments. At the same time, the study identified challenges related to swarm size scalability in narrow spaces, defining directions for further improvements.

Keywords: unmanned ground vehicles, *A** algorithm, artificial potential field algorithm, dynamic environment, autonomous swarm navigation

1. Introduction

Autonomous unmanned ground vehicles (UGVs) have greatly impacted tasks that were once labor-intensive and dangerous and are rapidly changing the way people do things across a wide range of applications, from automating agricultural tasks [1] and inspections in construction and infrastructure [2], to carrying out dangerous jobs such as explosives disposal [3]. In addition, they are at the very heart of revolutionizing transportation processes, particularly in addressing the "last-mile" delivery challenge [4], and they cannot be replaced when it comes to search and rescue missions and expeditions in places with untrusted terrain [5].

In terms of efficiency, the higher one is achieved when going from single agents to coordinated groups, called robot swarms. This idea is borrowed from the collective behavior of natural systems,

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for example, insect colonies or bird flocks, and allows a single agent to tackle a problem that is beyond its capability. The main advantage of a swarm is that the decentralized nature allows the complex global actions to emerge from the simple, local interactions of the individual agents, so, there is no need for a central control node.

Despite considerable progress, many existing approaches to swarm control rely on static methods. Nevertheless, their application potential is constrained in real-world situations that are very dynamic due to the presence of unexpected obstacles. This clearly demonstrates the need to improve the current algorithms and develop new ones that are not only efficient in navigation but also highly scalable and adaptable.

So, the importance of this study is outlined by the necessity to connect the gap between the theoretical swarm intelligence concepts and the actual demands of the dynamic environments. This research is focused on the enhancement of existing approaches to make them capable of operating under constantly changing conditions that improve the efficiency and reliability of current assignments and allow deploying swarm technologies in fundamentally new scenarios that are currently considered unreachable.

2. Literature review and problem statement

Modern methods of path planning for autonomous ground vehicles are changing at a fast pace, a trend that is confirmed by a review [6] that evaluates 15 commonly used algorithms. The authors classify these algorithms according to the scope of application: for the global planning, for example, *A** algorithm, for the local planning, for instance, artificial potential field (APF) method and intelligent methods, applicable to both categories include particle swarm optimization (PSO) or deep reinforcement learning (DRL) approaches. The emergence of hybrid algorithms is one of the major trends which the paper emphasized. To illustrate, in these kind of systems traditional methods such as *A** are merged with intelligent approaches like genetic algorithms or DRL approach in order to gain synergistic effects and improve performance. The authors of the article have opinion that the future of the area is in the combination and co-optimization of several algorithms, where intelligent and optimization-based methods will have more influence.

Despite the maturity of classical algorithms, researchers continue to explore ways for their improvement. For instance, the work [7] proposes a multi-stage, *A**-based method for route planning in autonomous logistics systems. Firstly, a modified *A** algorithm finds a safe preliminary route by taking into account distance to the obstacles and road markings. After that, *k*-means clustering is applied to find dangerous parts of the track like sharp turns. Next, these segments are smoothed with *Bézier* curves, and at the same time, the problem of the oncoming lane is solved by changing the trajectory to its mirror image. For adapting to dynamic obstacles in real time, a reinforcement learning model is added, which allows the execution of local maneuvers. As a result, this approach ensures the avoidance of potentially dangerous situations and significantly enhances navigational safety and flexibility. However, the method is exclusively focused on single-agent applications, leaving the swarm system coordination challenge open for the future work.

In contrast, the research [8] focuses on controlling a swarm of automated guided vehicles (AGVs) in manufacturing environments. Trajectory planning for individual agents is achieved using a potential field-based controller that generates conflict-free routes. To achieve this, the controller accounts for attractive forces from target workstations and repulsive forces from obstacles and system boundaries. Nevertheless, this method is based on the traditional APF technique, which suffers from the local minima issue. Although the writers mention that this problem was not present in their experiments, it is still important to note that the setting they used for testing was quite straightforward and did not contain the complicated barriers that usually generate such difficulties.

The local minima issue in the APF method has been approached in a number of unconventional ways that attempt to find a solution. For example, the study [9] introduces a hydrodynamics-inspired method, where the terrain becomes an “artificial pool”, the vehicle is a particle with negligible weight and the target is a “drain” that generates the fluid flow. Unlike the standard APF method, this approach guarantees that the target will be reached, successfully bypassing the bottlenecks typical for

U-shaped obstacles and narrow passages. However, the work is predicated on the assumption of a static environment. This is because modeling fluid dynamics by solving the *Navier-Stokes* equations is computationally intensive and performed only once for a known map. Hence, a change in the obstacles would require a total recalculation of the flow, that being highly impractical for real world applications.

In order to solve the problem of local minima in dynamic situations, especially with the unpredictable obstacle, the research [10] suggests an improvement to the APF method. The algorithm finds local minimum traps by looking at the differences in the system's total potential energy. When such a case is detected, the method temporarily creates a "second virtual target" in an adjacent lane to allow the vehicle to carry out a passing maneuver. Though this algorithm has been confirmed as effective by simulations conducted in MATLAB and CarSim, it is very narrowly targeted in terms of its use. The approach is essentially based on the assumption that there are distinct lanes in a highly organized road system, which limits the scope of the method to only those areas that are structured.

The local minimum problem is a challenge not only for ground systems but for vehicles in aquatic environments as well. For example, the study [11] is an instance that extends in the scope of underwater drones formation control by employing a four-level hierarchical system. At the behavioral level of this framework, the APF method is applied for target following and obstacle avoidance. The main intention for this paper, however, is on kinematic planning. It does not explain how the control vectors which are produced by the potential field are translated into the actual commands for the vehicles, so, this important part in the paper has left a significant void between the high-level planning and the low-level dynamic control.

The idea of hierarchical algorithms mixing is further discussed in the paper [12], where the hybrid bidirectional *A** with a modified artificial potential field (B*A**-MAPF) algorithm for unmanned ground vehicles is introduced. For global planning, an enhanced *A** algorithm is utilized. It employs a bidirectional search strategy to reduce computation time, interpolation to eliminate redundant nodes, and *B*-spline smoothing to refine the final trajectory. Meanwhile, the APF method, responsible for local planning, has been modified to overcome the local minima problem by adjusting the repulsive field function and introducing a distance coefficient into the attractive field function. The hybrid nature of the approach lies in the strategy of switching from the global planner to the enhanced APF method upon detecting dynamic obstacles near the planned route. Simulation results also showed that the suggested algorithm is better than the standard *A** and APF methods in terms of path length, trajectory smoothness, and computation time in different static and dynamic environments. Nevertheless, the method still has some limitations because it works with a simplified grid model of the environment, which only allows cells to be "passable" or "impassable". This representation, however, quite inaccurately describes the situation in the real world. A more realistic method would involve the cost of traversing each cell so that the path planning that is best in terms of energy, time, or safety could be performed.

The literature review that has been completed brings out an important topic in present-day planning research. On the one hand, there are classical algorithms that are computationally efficient, but at their very core, they have flaws, like the local minima problem in the APF method. On the other hand, we were able to observe the development of more complicated and modified methods which are frequently very specialized in their application to some particular conditions (such as structured road environments) or are based on unrealistic assumptions (for example, simplified environment models). Moreover, a lot of articles are still very focused on single-agent systems and do not have scalable mechanisms to coordinate swarms in complicated and changing environments.

While some studies have been carried out and are still going on, the general knowledge about solutions that can take into account all of the complexities that the environment imposes is still quite limited. This situation highlights the urgent need of the search for a scalable path-planning method for unmanned ground vehicles swarm that incorporates the realistic terrain costs and guarantees a reliable real-time response to the changes in the environment, addressing limitations of the existing approach.

3. The aim and objectives of the study

The object of this study is the process of path planning and navigation for unmanned ground vehicles swarm within a complex and dynamic two-dimensional simulated environment. The swarm operates as a single, coordinated system with a main task of moving from a starting point to a destination point while maintaining a predefined formation and avoiding collisions.

The aim of this research is to develop a path planning algorithm for the autonomous navigation of unmanned ground vehicles swarm. This method should utilize a hybrid approach to enhance the efficiency of obstacle avoidance and improve adaptation to dynamic environments.

To achieve this aim, the following objectives have been defined:

– to develop method for the path planning for unmanned ground vehicles swarm in the proposed dynamic environment and perform its simulation;

– to develop dynamic environmental model characterized by the presence of both static and dynamic obstacles, as well as a surface with varying traversal costs.

4. The study materials and methods for hybrid path planning

4.1 The subject and hypothesis of the study

The subject of this research is a hybrid path planning algorithm that integrates a global planner based on the $A*$ algorithm with a local planner based on the APF method. The study investigates how the selection of $A*$ algorithm for global path planning in a cost-aware environment and the use of APF for real time adapting to the local conditions (such as static and dynamic obstacles or other members of the swarm) can give rise to a synergistic effect.

The main hypothesis of this research states that a hybrid method can provide better performance in navigational efficiency and safety for unmanned ground vehicles swarm in dynamic environments than the deployment of a single one. This approach combines the strengths of global path lookup, using a modified $A*$ algorithm, able to handle terrain costs, with local navigation, using the APF method for real-time collision avoidance. It is expected that this combination will facilitate near-optimal paths discovery (because of $A*$ usage) while simultaneously ensuring the ability to avoid unexpected obstacles or intra-swarm collisions (due to APF usage).

This main hypothesis can be broken down into two hypotheses focusing on specific aspects.

The first hypothesis (*H1*) admits that the hybrid mode enables the swarm to reach its destination point faster and with a shorter total path length compared to relying solely on the APF method. The theoretical basis for this hypothesis is in the local minima issue that the APF method has. In complex environments, especially those with *U*-shaped obstacles, a swarm that is controlled by APF only method can find itself stuck in the condition where the attractive and repulsive forces are at a balance, hence no movement. The global path created by $A*$ algorithm acts as a guide that helps the swarm to escape from these traps and go along the globally optimal route.

The second hypothesis (*H2*) addresses the issue of scalability. It is expected that the hybrid approach will exhibit superior scalability as the number of vehicles in the swarm increases. The global path should provide a stable framework for the entire swarm's movement. In contrast, with a pure APF approach, an increase in the number of agents escalates the complexity of their mutual repulsive forces, potentially leading to more chaotic and less predictable motion.

4.2 Hybrid path planning method for unmanned ground vehicles swarm

The proposed hybrid approach to swarm navigation is based on a two-level architecture that consists of a global and local planner. This structure allows an effective distribution of computational tasks: strategic planning is performed once, while the tactical response to environmental changes occurs continuously at each step of the simulation.

At the global level, the responsibility for finding an optimal route from the starting point to the destination point is assigned to the $A*$ search algorithm. $A*$ is a classical graph search algorithm that has gained widespread adoption due to its completeness, optimality, and efficiency. Its core principle involves minimizing an evaluation function $f(n)$ for each cell n on the map:

$$f(n) = g(n) + h(n), \tag{1}$$

where $g(n)$ is the cost of the path from the start cell to the current cell n, and $h(n)$ is the heuristic function that estimates the cost of the path from cell n to the destination cell. The *Chebyshev* distance is used for the heuristic, assuming the target position coordinates are defined as (x_{goal}, y_{goal}):

$$h(n) = max\{|x_{goal} - x_n|, |y_{goal} - y_n|\}. \tag{2}$$

A standard implementation of A^* assumes a uniform cost for moving between adjacent cells (typically 1 for orthogonal moves and $\sqrt{2}$ for diagonal ones). However, in real-world conditions, traversing different types of terrain involves varying levels of difficulty. To account for this factor, the concept of a traversal cost is introduced. The key distinction of this approach, therefore, lies in modifying the calculation of the path cost, $g(n)$, to incorporate this value. Specifically, the cost of moving from a current cell n to an adjacent cell $n + 1$ is calculated by factoring in the terrain weight of the destination cell:

$$c(n, n + 1) = d(n, n + 1) \times w(n, n + 1), \tag{3}$$

where $d(n, n + 1)$ is the geometric distance between the centers of the cells, and $w(n, n + 1)$ is the terrain cost coefficient, which is predefined in the map configuration. For example, we can consider a cost of 1 for a hard surface like asphalt, 5 for moderately difficult terrain such as a grass area, and 10 for difficult-to-traverse terrain like mud. Cells designated as impassable are assigned an infinite cost and are excluded from the search space. Consequently, the A^* algorithm finds a path that is optimal not in the terms of its geometric length, but rather its cumulative traversal cost.

Once the path lookup is complete, and sequence of cells has been found, a path simplification procedure is applied. This procedure utilizes *Bresenham's line* algorithm to check for a direct line-of-sight (LoS) between waypoints on the path. This procedure iteratively prunes intermediate waypoints. If a direct, unobstructed line-of-sight exists between the start and end points of a path sequence, all points in between are removed. This process compresses the path into a concise set of key waypoints, significantly reducing the amount of data the local planner needs to process.

The global path, now represented as this set of key waypoints, is then passed to the local control level. In a swarm with N members, one vehicle is designated as the leader, which is tasked with moving sequentially between these waypoints. The other vehicles, acting as followers, do not navigate directly toward the global goal. Instead, their objective is to maintain a predefined formation relative to the leader's current position. The target position for each follower is dynamically calculated at every time step as a vector offset from the leader's position. The geometry of each formation offers distinct advantages depending on the mission assigned to the swarm. Among the formations considered in this study are the line formation (Figure 1*a*), where vehicles move in single file, making it suitable for navigating narrow passages such as tunnels, and the *V*-shape formation (Figure 1*b*), which is better suited for environmental exploration as the vehicles do not obstruct one another's field of view.

a *b*

Fig. 1. Swarm formation for 5 members: *a* – line; *b* – *V*-shape formation.

In summary, the hybrid framework operates as follows: the A^* algorithm determines the strategic path for the entire swarm, overseeing the whole map, while local algorithms handle the immediate, tactical movement and interaction of the vehicles within the formation.

4.3 Method for avoiding obstacles and collisions in the swarm

To implement motion at the local level, avoid collisions with static and dynamic obstacles, and prevent intra-swarm collisions, the APF method is employed. The core concept of APF treats each vehicle as a point mass moving within a vector field. In this field, the target generates an attractive force, while obstacles and other vehicles generate repulsive forces. The resultant force vector, F_{net}, which is the sum of all forces acting on the vehicle, determines its direction and velocity at the current time step:

$$F_{net} = F_{att} + F_{obs} + F_{UGV}. \tag{4}$$

Let us examine each component of this resultant force individually. The attractive force, F_{att} directs a vehicle toward its current target. This target is role-dependent within the swarm, so for the leader vehicle the target is the next key waypoint p_{goal} on the global path and this force is calculated with goal attraction coefficient, K_{goal}. For a follower vehicle, the target is its ideal position within the formation, p_{form} and this force is calculated with the formation attraction coefficient, K_{form}:

$$F_{att} = \begin{cases} K_{form}\left(p_{form} - p_j\right), \ UGV_j \ is \ follower \\ K_{goal}\left(p_{goal} - p_j\right), \ UGV_j \ is \ not \ follower \end{cases}, j \in \{1,2,\dots,N\}. \tag{5}$$

The next component is the repulsive force generated by obstacles, F_{obs}. This force is created by every static (for example, wall) or dynamic obstacle that falls within a predefined influence radius R_{obs}. The magnitude of the force is inversely proportional to the distance to the obstacle, increasing towards infinity upon close approach. The total repulsive force from obstacles is the vector sum of forces from all obstacles detected within the influence radius. It is calculated using the obstacle repulsion coefficient K_{obs} and the distance $d_{jk} = \|p_j - p_k\|$ between the vehicle j and obstacle k as described by the following formula:

$$F_{obs} = \sum_k \begin{cases} K_{obs}\left(\frac{1}{d_{jk}} - \frac{1}{R_{obs}}\right)\frac{1}{d_{jk}^2}\frac{p_j - p_k}{d_{jk}}, \ \ if \ 0 < d_{jk} < R_{obs} \\ 0, \ \ if \ d_{jk} \geq R_{obs} \end{cases}. \tag{6}$$

This formulation ensures that the force increases smoothly as the vehicle approaches an obstacle and drops to zero once the obstacle is outside the defined radius of influence.

To avoid intra-swarm collisions and maintain a safe distance between vehicles, an inter-agent repulsive force, F_{UGV}, is introduced. Its calculation is analogous to the obstacle repulsive force but utilizes a different set of parameters for its influence radius and repulsion coefficient. The total repulsive force exerted on a vehicle i is the vector sum of forces from every other vehicle j in the swarm, calculated based on the distance d_{ij} between them. This force is computed as follows:

$$F_{UGV} = \sum_{\substack{i=1 \\ i \neq j}}^{N} \begin{cases} 5K_{UGV}\frac{p_j - p_i}{d_{ij}}, \ \ if \ d_{ij} \leq R_{safe} \\ K_{UGV}\left(\frac{1}{d_{ij}} - \frac{1}{R_{UGV}}\right)\frac{1}{d_{ij}^2}\frac{p_j - p_i}{d_{ij}}, \ \ if \ R_{safe} < d_{ij} \leq R_{UGV} \\ 0, \ \ if \ d_{ij} > R_{UGV} \end{cases}, \tag{7}$$

where R_{UGV} is the inter-agent sensitivity radius, and R_{safe} is the safety radius that triggers an emergency mode. This mode is activated when vehicles get dangerously close (i.e., when the distance $d_{ij} \leq R_{safe}$). In this event, a significantly stronger repulsive force is engaged to guarantee collision avoidance: the inter-agent repulsion coefficient K_{UGV} has increased fivefold.

After calculating the total force vector F_{net}, it must be converted into a displacement vector for the vehicle. At this stage, a maximum velocity limit, which depends on the terrain type, is enforced:

$$v_{limit} = \frac{v_{max}}{cost(p_{UGV})}, \tag{8}$$

where v_{max} is the vehicle's maximum velocity, and $cost(p_{UGV})$ is the cost of the current cell. If the magnitude of the calculated force vector, $\|F_{net}\|$, exceeds this limit v_{limit}, the vector is normalized and scaled down to match v_{limit}.

Finally, a conflict resolution protocol is incorporated within the system. Before any vehicle proceeds, the system verifies whether its intended trajectory would cause an overlap with another one. If a potential intersection is detected, the movement of one of the vehicles (the one with the higher identity) is cancelled by setting its displacement vector to zero. This ensures safe and coordinated movement and helps to prevent collisions between vehicles in the swarm.

4.4 Simulation environment

The experiments were intended to test the effectiveness, reliability, and scalability of the implemented algorithm, and to confirm the scientific hypotheses *H1* and *H2* given before. To perform those experiments and validate the hybrid algorithm, a dedicated simulation setup was created using the *Python 3* programming language. The environment's architecture is based on several core libraries that provide the required functionality: *numpy* enables fast vector and matrix operations, which are crucial for calculating forces and positions; *matplotlib* is used for the live demonstration of the simulation and for the final results drawing. Finally, the *pathfinding* library offers a base implementation of the A^* algorithm, which was extended for this research to account for terrain weights. All simulations were performed on an ASUS VivoBook laptop (model X571LH). The system is equipped with an Intel Core i5-9300H CPU @ 2.2 GHz, 16 GB of RAM, and an NVIDIA GeForce GTX 1650 graphics card with 4 GB of GDDR6 memory, running on a 64-bit Windows 10 Pro operating system (version 10.0.19045).

An environment was defined as a 256x256 discrete grid, where each cell has a particular cost of movement. It is designed to represent different types of terrain: low-cost hard surface, medium-cost grass area, high-cost mud that makes movement considerably difficult and impassable walls with an infinite cost. The map configuration, which determines the distribution of these areas, is loaded from an external JSON file, thus allowing both flexibility and repeatability of the experiments. The map used in experiments was inspired by the urban layout of a district in the city of Kyiv, Ukraine.

To introduce an element of realism, the produced simulation had additionally a virtual environment where moving obstacles were also present. To each of the obstacles were attributed an initial position, velocity, and a route for the movement that is a series of waypoints. At each simulation step, obstacles move along their designated paths at a constant speed. Thus, they become the dynamic element of the environment.

The swarm can keep one of the predefined formations, such as line or *V*-shape as well as the distance between the members which was initially set. The exact number of unmanned ground vehicles in the swarm is specified by a simulation. One vehicle is randomly chosen as the leader, while the rest vehicles are the followers. Each vehicle is characterized by its physical radius, a sensor with limited range and a maximum velocity that is allowed.

5. Results of the research on hybrid path planning method

The primary outcome of this research is a hybrid method for the navigation of unmanned ground vehicles swarms. The developed algorithm is based on the synergy between two navigation approaches: global planning using the A^* algorithm and local control using the APF method. The scientific novelty is the fact that the approach is not just a combination of these methods, but their very particular integration for the purpose of control for the swarm of unmanned ground vehicles.

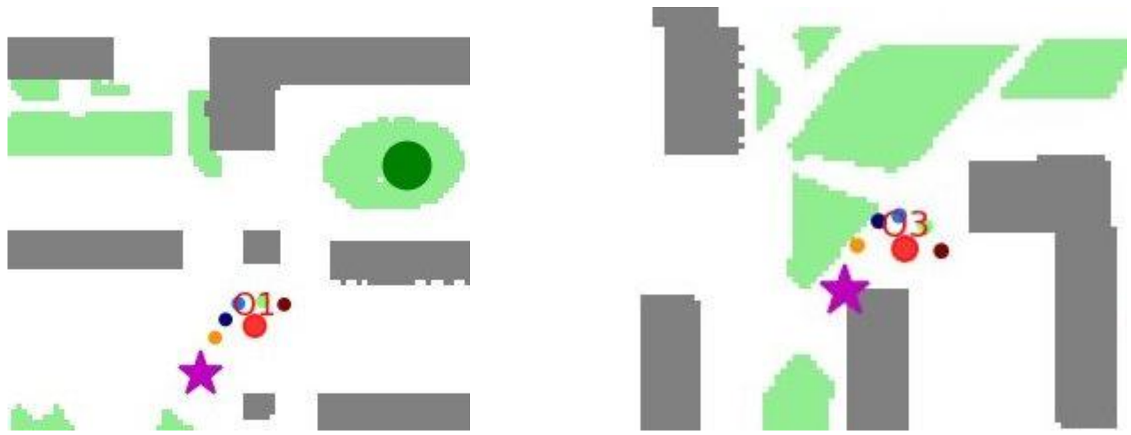
In the course of this study, the developed environmental model implemented a concept that was a departure from the one conveyed in research [12], adding an approach by which each cell is given a traversal cost, thus enabling path planning optimizations. And in a different manner from the work [11], it also provides for the presence of dynamic obstacles. This required an enhancement of the APF algorithm that became capable of avoiding collisions with all types of obstacles.

5.1 Simulation of the proposed method for the hybrid path planning

All results have been produced with the help of a simulator, which allowed the execution of controlled experiments in reproducible conditions. The research methodology included defining a baseline scenario and then carrying out several experiments by changing only one parameter at a time. This approach allowed the researchers to obtain reliable data for comparison since the influence of other factors on the system's behavior was isolated. To increase the statistical strength of the findings, each scenario was carried out three times, and the resulting metrics were averaged.

The baseline scenario for the experiments was defined with the following parameters: the simulation was conducted on the standard map with five vehicles swarm, maintaining line formation. The hybrid path planning mode was activated, and dynamic obstacles were enabled. Several key metrics were collected during the simulations to evaluate the effectiveness of the proposed approach. These included: the total number of simulation steps, path lookup time and final path length and cost.

A key experiment designed to showcase the hybrid algorithm's capabilities was a simulation conducted in a dynamic environment. In this particular case, the map was populated with several moving obstacles, where each one moved along a path that was meant to cross the expected route of the swarm. The experiment was an attempt to see if the hybrid method can respond in real time to the unexpected changes in the environment. The swarm, while heading to the intermediate waypoint (indicated by a star), is avoiding dynamic obstacle *O1*, that is shown on the Figure 2*a* and dynamic obstacle *O3*, that is depicted in Figure 2*b*.



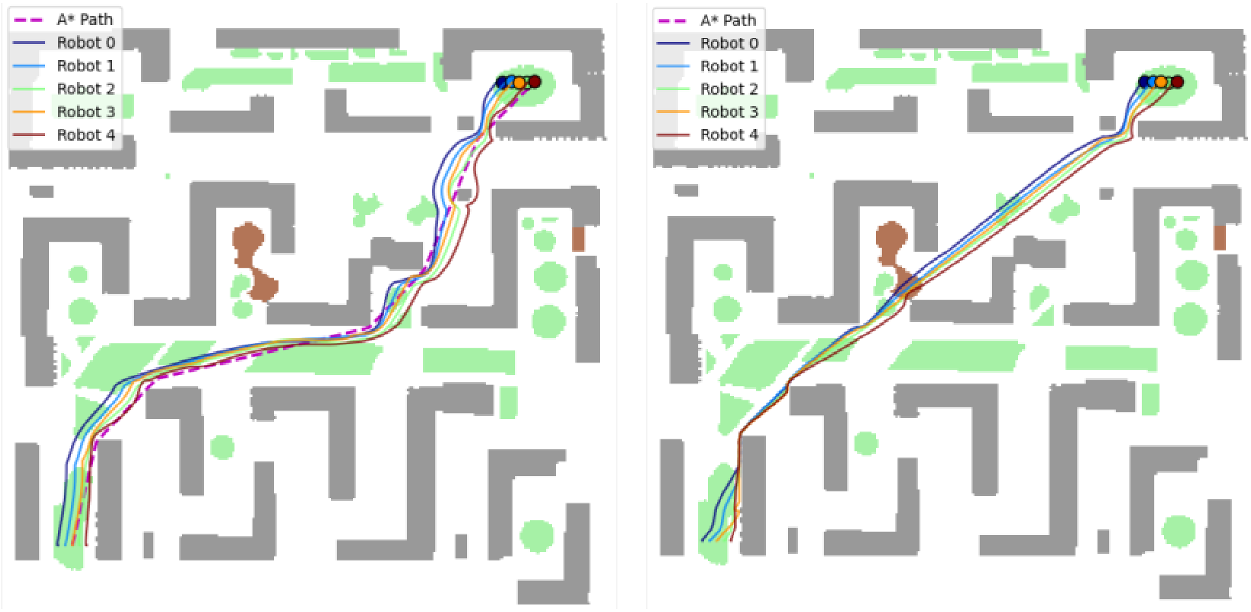
a *b*

Fig. 2. Swarm avoids dynamic obstacles: *a* – obstacle *O1* moves from right to left; *b* – obstacle *O3* moves from left to right.

When a mobile obstacle was detected near the trajectory of the swarm, the local APF planner produced the repulsive forces that caused the vehicles to be redirected briefly from their way. It should be noted that once the obstacle was avoided, the attractive forces towards the next waypoint returned the swarm to its trajectory and the formation was also recovered. This experiment definitely showed that an architectural concept that combines strategic global planning and tactical local response is very efficient while maneuvering in places where the environment state is not known initially.

5.2 Proposed method comparison with original artificial potential field algorithm

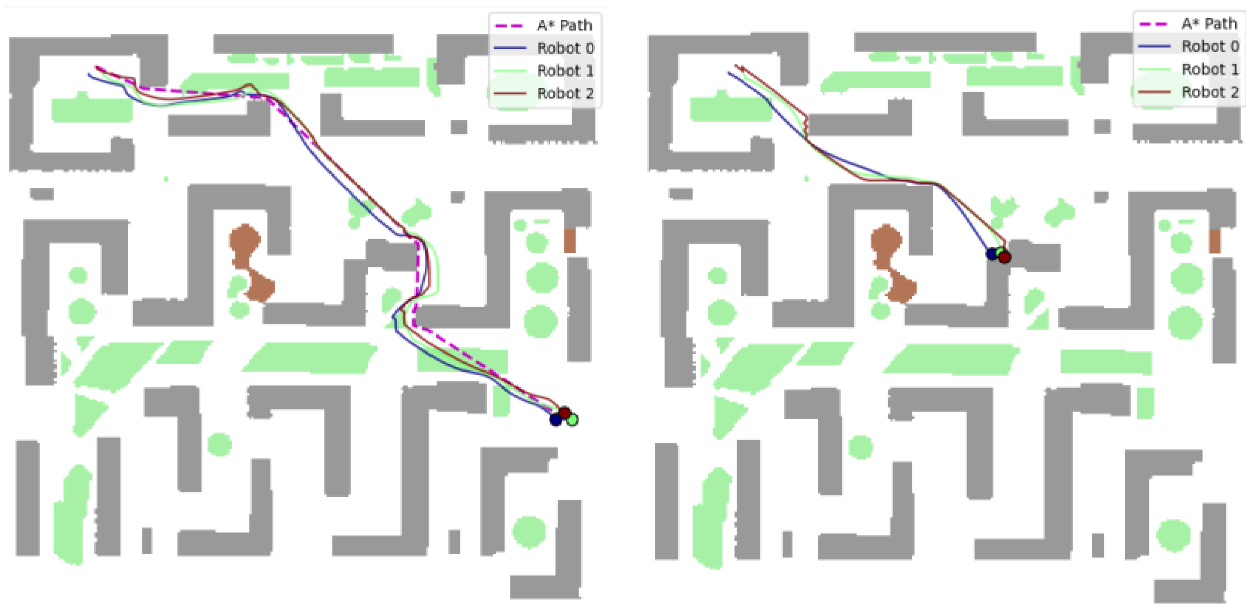
The research was designed around the performance comparison of two different modes of operation: the hybrid approach and the mode that uses only the APF technique. The gathered data, enriched with path visualizations, enabled the experimental validation of hypothesis *H1*. In the hybrid case global planner avoided areas with higher traversal costs (Figure 3*a*). In the pure APF case, the global planner was disabled, and the sole attractive force for the leader vehicle was the destination point. The results revealed that this method was able to locate shorter, but not optimal path, since it went via high-cost terrain, as depicted in Figure 3*b*.



a *b*

Fig. 3. Path comparison: *a* – hybrid approach avoids high-cost areas; *b* – pure APF approach found shorter, but not cost-efficient path.

On the other hand, the pure APF method is not always competitive when compared to the hybrid algorithm, since it performs well only with suitable starting and destination points. To illustrate, Figure 4*b* shows a scenario, where the APF-only approach could not come up with a solution because of the local minima problem. In contrast, the hybrid algorithm solves this problem, as depicted in Figure 4*a*.



a *b*

Fig. 4. Swarm path lookup: *a* – hybrid approach successfully found path; *b* – pure APF approach was stuck because of local minima problem.

Another experiment was dedicated to analyze swarm performance as a function of its size. A series of simulations, where the variable parameter was the swarm members number, ranging from 3 to 11 agents was conducted. Relationship between path planning success rate (i.e., scenarios where the leader reached the destination point), swarm size, and formation type is depicted in Figure 5.

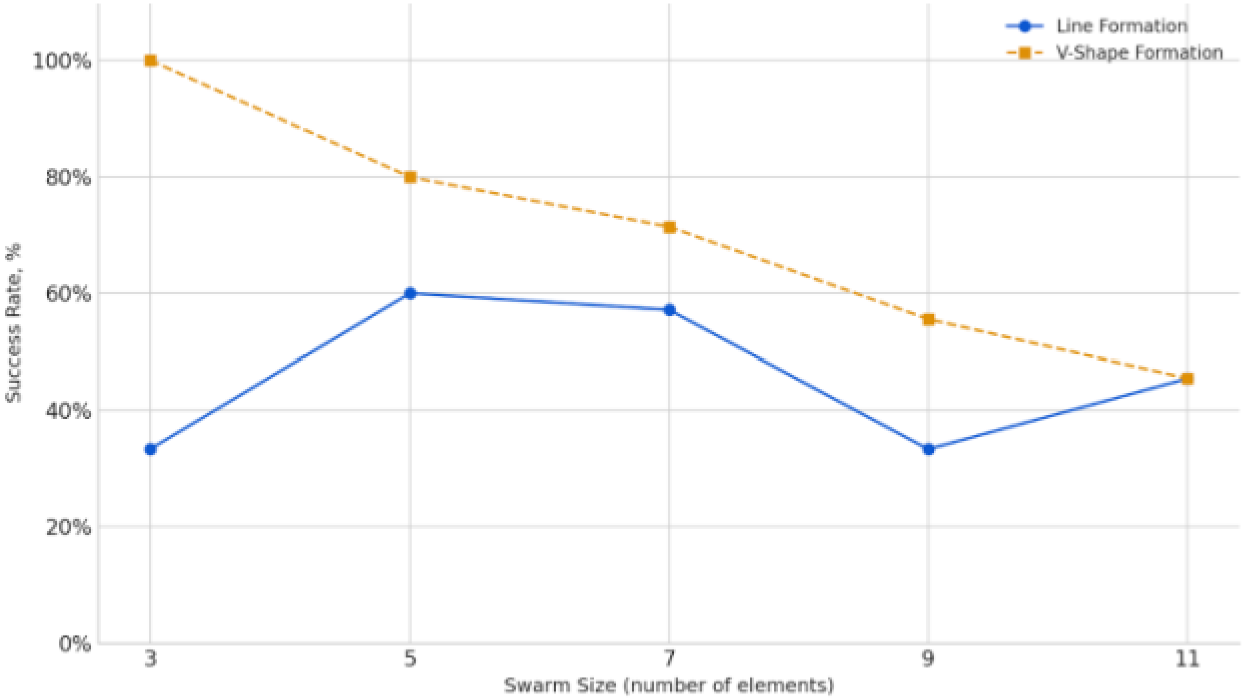


Fig. 5. Success rate of the hybrid algorithm depending on the formation size and type.

It is important to note, that in this series of tests, the pure APF approach was entirely unable to reach the destination due to the local minima problem; therefore, the experiment proceeded using only the hybrid approach.

6. Discussion of results for hybrid path planning method

This discussion is dedicated to interpret data from the previous section within the context of stated hypotheses. The first one (*H1*) stated that the hybrid mode is superior to the pure APF approach in terms of path optimality. The experimental data supported the assumption. The global path found by $A*$ algorithm practically breaks down a complicated navigation problem into a series of easier ones, where each intermediate waypoint is selected so that no local minima are generated.

It is worth noting an interesting aspect revealed during the experiment (Fig. 3), where the pure APF approach managed to find a geometrically shorter path. This can be explained if we consider that the global planner intentionally bypassed high cost areas, and thus, was able to achieve a minimum total traversal cost. On the other hand, the APF-only approach which did not have information about the cost was influenced only by the distance factor. So, the hybrid approach succeeds in path planning that is optimal to the specified criteria, which is cost for our case.

The second hypothesis concerning scalability (*H2*) has the results being more complex than expected. The experiments for the hybrid approach showed that the mission success rate decreases as the number of vehicles in the swarm increases. The reason why this happened is that the complexity of the APF-based interactions grows with the increase in the number of agents. The sum of the repulsive forces between the members of the swarm becomes so large that it becomes a problem to go through narrow passages. In such cases, the swarm becomes less maneuverable, and the local repulsive forces can overwhelm the attractive force toward the global goal, causing the swarm to halt.

Interestingly, the *V*-shape formation demonstrated better stability compared to the line formation. This is due to the fact that vehicles in the line are arranged more tightly, thus resulting in stronger repulsive forces between them while maneuvering. On the other hand, the pure APF-based method was completely incapable of handling the assignment in this experiment. Although the performance of the hybrid approach degrades with an increasing number of swarm members, it is still working, which proves its better scalability potential. So, hypothesis $H2$ is partially supported.

In this discussion, several focus areas for the future work can be highlighted. Major attention requires challenge to prevent decline in the mission success rates in the large swarm scenarios. A potential solution might employ an adaptive APF approach that control the inter-agent repulsion coefficient (K_{UGV}) to be gradually lowered as the swarm moves through a narrow passage. This would allow the swarm to "compress" itself temporarily for the navigation through the corridors. Another approach may involve dynamic formation switching, like changing from V-shape to line before entering a narrow passage.

Secondly, the proposed approach employs a static leader role, which might not work in real-world situations. Hence, there is a need to come up with a dynamic election mechanism, where the leadership role is automatically passed to another vehicle from the swarm in case of current leader failure. This would significantly enhance overall reliability and survivability of the swarm.

Finally, the ultimate step for the future work is transition from simulation to experimentation with physical robotic platforms. This is essential to confirm the capability of the approach in a practical scenario. Testing on physical hardware will enable a final decision to be made about the usefulness and applicability of the suggested hybrid approach in the real world.

Conclusions

This research focused on ensuring efficient, reliable, and scalable movement of unmanned ground vehicle swarms in dynamic environments. This paper proposes a hybrid real-time path planning method in complex environments, which combines the advantages of global planning, implemented by a modified $A*$ algorithm, with local control based on the enhanced APF method. The APF method improvements, adapted to swarm interaction tasks, have enabled several features typical for dynamic environments, including following the leader, obstacle avoidance (both static and dynamic), maintaining the specified formation, and avoiding collisions within the swarm.

Upon completion of the theoretical and experimental stages of the study, it may be stated that all objectives have been achieved. An environmental model that adequately reflects the difficulties of the real world was constructed. This was done by introducing maps with variable traversal costs and the implementing of dynamic obstacles that was a key element for path planning efficiency research in dynamic environments. The developed environmental model enabled evaluation of the hybrid path planning method's efficiency in real time.

The environmental model was implemented in the simulator, tailored to conducting multiple path planning experiments. The simulations confirmed the potential of the method. Results indicate that a swarm controlled by the hybrid approach reaches its destination, navigating the environment with moving obstacles while maintaining formation integrity.

This simulation study produced results, proving the hypothesis that the path found in hybrid mode is more efficient than the path found by pure APF approach was confirmed, and hypothesis about scalability of the hybrid approach that is superior to the pure APF approach showed both the positive and negative features of the proposed method. Experiments confirmed that the proposed hybrid approach was shown to be better than the pure APF method in terms of path cost. However, further comparative studies with other hybrid methods remain to be conducted. In conclusion, the developed approach has its strengths and weaknesses that have been directly acknowledged by the authors of the article and directions for the further work were formulated.

To sum up, this investigation contributes to the advancement of multi-agent systems. These findings can be applied in a range of areas where the coordinated collective action of unmanned ground vehicles is needed. The limitations encountered during this research provide starting points for the future work, such as the development of adaptive formation control and a dynamic leadership mechanism.

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МЕТОД ГІБРИДНОГО ПОШУКУ ШЛЯХУ ДЛЯ РОЮ БЕЗПІЛОТНИХ НАЗЕМНИХ РОБОТІВ В ДИНАМІЧНИХ СЕРЕДОВИЩАХ

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Наземні роботизовані комплекси (НРК) мають значний потенціал для різноманітного застосування, зокрема для автоматизації агротехнічних робіт, інспекції та технічного обслуговування на будівництві та промисловості, для автоматизації складних монтажних процесів та ремонту інфраструктури, для знешкодження вибухонебезпечних предметів, для автоматизації логістичних процесів, для вирішення завдань пошуково-рятувальних операцій, а також для експедицій у важкодоступних регіонах. Проте на шляху їх впровадження стоїть проблема автономної навігації, яка становить серйозний виклик через постійні зміни розташування перешкод, непередбачувані сценарії та необхідність швидкого прийняття рішень для забезпечення безпеки й стабільності руху.

Об’єктом дослідження цієї статті є процес гібридного пошуку шляху під час автономної навігації моделі рою наземних роботизованих комплексів у симуляційному середовищі. Метою дослідження є створення методу автономної навігації для рою наземних роботизованих комплексів з використанням методу гібридної навігації, що забезпечує підвищення ефективності уникнення перешкод та адаптацію до динамічного середовища.

Для досягнення даної мети запропоновано новий метод для автономної навігації рою на базі гібридного підходу, який відрізняється від відомих рішень тим, що для навігації на глобальному рівні використовується алгоритм пошуку A*, що враховує ціну прохідності на карті, а для навігації на локальному рівні використовується алгоритм штучних потенційних полів, що підтримує лінійну та V-подібну формацію рою.

Результати дослідження показали, що використання запропонованого методу дозволяє рою будувати оптимальні маршрути з урахуванням вартості пересування та уникати проблеми локальних мінімумів, притаманної методу штучних потенційних полів. Метод успішно проявив себе в стимуляційному середовищі, тому можна зробити висновок про потенціал подальших досліджень в реальних умовах та застосувань у сфері ройових безпілотних систем у мінливих середовищах. Водночас дослідження виявило виклики, пов’язані з масштабованістю рою у вузьких просторах, що визначає напрями для подальших удосконалень.

Ключові слова: наземний роботизований комплекс, алгоритм *A**, алгоритм штучного потенційного поля, динамічне середовище, автономна навігація рою.