Optimizing Collision Avoidance in Dynamic Multi-Robot Systems: A Velocity Obstacle and BB-PSO Approach with Priority Consideration

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Keywords: Multi-Robot Systems, Prioritized Navigation, Collision Avoidance, Velocity Obstacles, Particle Swarm Optimization.

Abstract: This study proposes integrating Reciprocal Velocity Obstacles (RVO) with Bare Bones Particle Swarm Optimization (BB-PSO) for prioritized motion planning in multi-robot systems. BB-PSO was chosen because it has fewer parameters to tune, reduced computational complexity, and provides potentially faster convergence compared to standard PSO. The methodology enables collision avoidance and path planning while allowing differentiated robot behaviors based on priority levels. Simulations used a two-phase experimental strategy: first, tuning cost function parameters through grid search, and second, evaluating various priority configurations and random scenarios. Results show that the selected weight configuration ($\alpha = 4, \beta = 2$) balances goal-seeking and obstacle avoidance, enabling high-priority agents to move directly while ensuring overall group safety. Scenarios with higher average priorities exhibited shorter travel distances and faster completion times, whereas those with lower or imbalanced priorities led to more conservative behavior and delays. Compared to a greedy baseline, the proposed method significantly reduced collisions, achieving an average of 1.0 collision per scenario versus 6.6 with the greedy approach. Some priority configurations achieved complete task fulfillment without any collisions, highlighting the potential for optimized multi-robot coordination. The proposed method offers a promising strategy for prioritized motion planning, balancing efficiency and safety based on task importance. Future research includes comparing BB-PSO with other optimization methods, reducing sample requirements, dynamically adjusting priorities, and extending the model to incorporate task parameterizations and autonomous priority adaptation.

1 INTRODUCTION

Motion planning in robotics involves determining a sequence of movements that allow a robot to navigate from an initial position to a desired goal while avoiding obstacles. This essential aspect of robotics requires computing a collision-free path through the robot environment, accounting for kinematics, dynamics, and environmental constraints (Latombe, 1991). Even in its simplest form, where a rigid object navigates among static obstacles, the problem is NP-hard (Canny, 1988) and its complexity increases in the presence of dynamic obstacles, deformable bodies, or multiple robots.

This work addresses the Multi-Robot Motion Planing Problem (MRMP) (Saha and Isto, 2006), while prioritizing the motion of certain robots over others, with the goal of enabling efficient, coordinated navigation where some agents are granted passage preference owing to task urgency, resource constraints, or mission-critical roles.

A central challenge in multi-robot systems is coordinating robot motion to prevent collisions and ensure efficient operation. Effective coordination enables robots to move simultaneously without unnecessary delays, thereby demanding quick decisions in dynamic settings. The complexity of MRMP increases exponentially with the number of robots, owing to the expansion of the joint configuration space. Researchers have explored various strategies, including centralized and decentralized approaches, sampling-based algorithms, and optimization techniques (Sanchez and Latombe, 2002). Among the recent trends, heuristic and AI-based methods have demonstrated improved adaptability and efficiency. Bio-inspired strategies, as reviewed by Banik et

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Sanchez-Vaca, L. H., Sanchez-Ante, G. and Abaunza, H.
Optimizing Collision Avoidance in Dynamic Multi-Robot Systems: A Velocity Obstacle and BB-PSO Approach with Priority Consideration.
DOI: 10.5220/0013720000003982

In *Proceedings of the 22nd International Conference on Informatics in Control, Automation and Robotics (ICINCO 2025) - Volume 2*, pages 309-316
ISBN: 978-989-758-770-2; ISSN: 2184-2809

al. (Banik et al., 2025), highlight the growing interest in hybrid approaches that blend heuristics with AI to enhance performance in dynamic environments.

Chen et al. (Chen et al., 2024) present a velocity prediction algorithm combining backpropagation (BP) neural networks with reciprocal velocity obstacles (PRVO). This method predicts velocities to reconstruct the velocity obstacle region and optimizes robot navigation in dense and dynamic environments. Likewise, Jathunga and Rajapaksha (Jathunga and Rajapaksha, 2025) proposed a hybrid Probabilistic Roadmap (PRM) method enhanced with Genetic Algorithms (GA), termed PRM-GA. Their approach improves the path quality by reducing the path length and turn count, outperforming traditional PRMs in dynamic environments.

Task prioritization is also critical in multi-robot systems, particularly when resources are limited or mission objectives vary in urgency. For instance, in search and rescue missions, it is vital to prioritize robots that locate survivors over those that clear debris (Banik et al., 2025). Dynamic task prioritization requires the adaptation of priorities based on real-time performance metrics, which can be computationally intensive, but is essential for maintaining system efficiency (Guo et al., 2018). Tian et al. (Tian et al., 2021) explored real-time path planning using wireless sensor networks and enhanced AI algorithms, stressing the importance of adaptive prioritization to avoid delays and ensure continuous operation.

Another challenge lies in learning task priorities from demonstrations. Extending models to incorporate task parameterizations and enable autonomous priority adaptation are essential for enhancing robot autonomy (Silvério et al., 2018). Kumar et al. (Kumar et al., 2023) introduced a hybrid controller that combines artificial bee colony optimization with recurrent neural networks, thereby achieving significant improvements in navigation performance in unknown environments.

Prioritized motion planning assigns priority levels to robots based on criteria, such as task urgency or energy constraints. Higher-priority robots plan their paths first, whereas others adjust their trajectories accordingly. This sequential strategy simplifies computation compared to centralized methods, but can limit the solution space for lower-priority robots, potentially leading to suboptimal routes.

The velocity-obstacle (VO) approach is widely used in mobile robotics for motion planning and collision avoidance. VO defines sets of velocities that would result in a collision and represents them geometrically in the velocity space. By selecting velocities outside these regions, robots can navigate safely in dynamic environments (Fiorini and Shiller, 1998). This method extends naturally to multi-robot systems by treating each robot as a moving obstacle, enabling decentralized coordination.

An important refinement of VO is the Reciprocal Velocity Obstacles (RVO) approach, which assumes mutual collision avoidance between robots. Van den Berg et al. (Van den Berg et al., 2008) introduced RVO to improve navigation efficiency by considering reciprocal behavior. Further developments, such as Optimal Reciprocal Collision Avoidance (ORCA) (Alonso-Mora et al., 2013) enhance RVO by integrating optimization methods, resulting in smoother and more robust trajectories in dense environments.

Paikray et al. (Paikray et al., 2021) proposed an improved version of Particle Swarm Optimization (PSO) using sine and cosine algorithms (IPSO-SCA) to generate optimal deadlock-free paths. Their method balances exploration and exploitation while minimizing individual path lengths, underscoring the robustness of PSO in dynamic and cluttered scenarios.

1.1 Problem Statement

The Velocity Obstacle (VO) approach is an effective framework for constructing motion plans for multiple robots. Several VO variants have emerged that focus on optimal trajectory generation. This study proposes a novel VO variant guided by Particle Swarm Optimization (PSO) to enhance local decision-making within the VO framework.

PSO is a population-based optimization algorithm inspired by the collective behavior of swarms such as bird flocks and fish schools. Each particle represents a potential solution, and navigates a multi-dimensional search space by adjusting its position based on personal and global bests. PSO's simplicity, adaptability, and efficiency make it suitable for addressing complex high-dimensional optimization problems. Besides, PSO has recently being applied to mobile robots, sometimes in hybrid approaches, as the one presented in (Najm et al., 2024), where the authors combine PSO with a Whale Optimization Algorithm (WOA). They found good reductions in path length with this approach. The versatility of PSO is such that in (Nasir et al., 2025), the PSO is used to fine tune the parameters of Fuzzy Logic Controllers. Its applications span robotics, engineering, and machine learning, particularly in parameter tuning, path planning, and feature selection.

1.2 Specific Goals and Scope of the Study

A key component of sampling-based MRMP is the tensor roadmap, which combines individual PRMs for each robot. Recent work introduces the "staggered grid" sampling scheme, which significantly reduces the number of required samples while maintaining near-optimality (Banik et al., 2025). This method demonstrates high-quality solutions with fewer samples in multi-robot scenarios (Jathunga and Rajapaksha, 2025) and outperforms uniform random sampling, particularly in low-sample regimes. Distributed navigation and obstacle avoidance strategies further enhance performance in complex, dynamic environments (Yang et al., 2023).

2 METHODOLOGY

2.1 System Model and Assumptions

Let us consider a set of N mobile robots that operate in a shared two-dimensional environment. Each robot R_i, where $i = 1,...,N$, is modeled as a disc-shaped holonomic agent with radius r, position $\mathbf{x}_i \in \mathbb{R}^2$, and velocity $\mathbf{v}_i \in \mathbb{R}^2$. Robots can select their velocity at discrete time steps, $t_k = k\Delta t$, where Δt is fixed. Each robot's motion follows simple kinematics: straight-line motion with constant velocity within each time step, subject to velocity and acceleration constraints. All robots are assumed to have the same size and capabilities.

We assume that all agents have access to the positions and velocities of other robots at all times. This capability allows reactive navigation and avoidance behaviors. However, each robot maintains its own private navigation goal $\mathbf{g}_i \in \mathbb{R}^2$. This approach resembles a real-world scenario in which agents can have sensing capabilities to detect other agents while maintaining a decentralized navigation system.

Each robot R_i is assigned a priority level $P_i \in [0,1]$. This scalar value represents the importance of an agent's task. Robots with higher priority are expected to maintain more direct trajectories toward their goals. Robots with a lower priority are expected to adjust their paths to avoid interference with higher-priority agents.

Priority values influence the weights of the cost functions used during the optimization. This mechanism enables implicit hierarchical coordination without requiring centralized control or explicit negotiation between robots.

2.2 Reciprocal Velocity Obstacle Formulation

To ensure safe navigation in a shared environment, each robot must avoid collisions with the other agents. We adopted the Velocity Obstacle (VO) framework to identify the velocities that would lead to a future collision if both agents maintain their current velocities.

The Velocity Obstacle is defined as follows. Let two robots, R_A and R_B, with current positions $\mathbf{p}_A$ and $\mathbf{p}_B$, velocities $\mathbf{v}_A$ and $\mathbf{v}_B$, and radii r_A and r_B, the VO for robot R_A induced by robot R_B is defined in Eq. 1.

$$VO_{AB} := \{\mathbf{v}_i \in \mathbb{R}^2 | \mathbf{v}_A - \mathbf{v}_B \in CC(\mathbf{p}_B - \mathbf{p}_A, r_A + r_B)\} \quad (1)$$

This equation implies that $\mathbf{v}_i$ lies within a collision cone (CC) of relative velocities that would result in a collision with R_B, assuming that both agents maintain a constant velocity. The cone is centered along the vector $\mathbf{p}_B - \mathbf{p}_A$, and its angular aperture is defined as the sum of $r_A + r_B$. Any velocity $\mathbf{v}_A$ within VO_{AB} would eventually bring robot R_A into contact with R_B.

However, in VO, avoidance is unilateral; robot R_A is responsible for avoiding R_B. When both agents try to avoid each other independently, this can lead to overly conservative behavior or oscillations. To address this, we adopted the Reciprocal Velocity Obstacles (RVO) formulation.

The key idea in RVO is to share the responsibility for collision avoidance between agents. Instead of avoiding the entire VO, each agent avoids only the portion of the velocity space that would lead to collision, assuming that the relative velocity is equally adjusted. The RVO for robot R_A with respect to R_B is defined in Eq. 2.

$$RVO_{AB} := \{\mathbf{v}_A \in \mathbb{R}^2 | \mathbf{v}_A - \frac{\mathbf{v}_A + \mathbf{v}_B}{2} \in VO_{AB}\} \quad (2)$$

Similarly, R_A avoids the VO region centered at the average velocity of both agents rather than at V_B. This formulation results in more balanced and natural agent interactions, reducing unnecessary detours and avoiding deadlocks in symmetric scenarios.

At each planning step, robot R_A generates a discrete set of velocity candidates V_A based on its dynamic constraints, known as Reachable Velocities (RV). We then filter this set by removing all velocities within the union of the velocity obstacles induced by neighboring agents, as shown in Eq. 3.

$$RAV_A := \{\mathbf{v} \in V_A | \mathbf{v} \notin U(VO_{AB})\} \quad (3)$$

The resulting set, the Reachable Avoiding Velocities (RAV), is the feasible domain for the subsequent optimization step. The following section describes how a Particle Optimization (PSO) strategy guides the velocity selection process.

2.3 Particle Swarm Optimization Algorithm

To select the optimal velocity from the set of safe candidates (RAV), we employ the Bare Bones Particle Swarm Optimization (BB-PSO) algorithm. This variant of PSO eliminates the use of velocity vectors and generates new candidate solutions by sampling a Gaussian distribution defined by the best-known positions.

Each robot runs an independent instance of BB-PSO at every time step to select the next velocity. The swarm comprises particles, each representing a candidate velocity, $\mathbf{v} \in \mathbb{R}^2$.

For each particle p, a new position is generated by sampling from the normal distribution given in Eq. 4.

$$\begin{aligned} \mu_p &= \frac{1}{2}(p_{best} + g_{best}) \\ \sigma &= |p_{best} - g_{best}| \\ x_p^{(t+1)} &\sim N(\mu_p, \sigma), \end{aligned} \tag{4}$$

Here, μ_p is the mean of the distribution, calculated as the average of the particle's best-known position (p_{best}) and the global best position among all particles (g_{best}). σ is the standard deviation, defined as the absolute difference between p_{best} and g_{best}. The new position $x_p^{(t+1)}$ is sampled from a normal distribution $N(\mu_p, \sigma)$.

The new position is considered only if it is a part of the RAV set. Otherwise, the particle will maintain the same position. This ensures that only valid velocities are generated for all particles during the optimization process. We evaluate each valid candidate velocity by using the cost function in Eq. 5.

$$\begin{aligned} J(\mathbf{v}) = \alpha \cdot \|\mathbf{g} - (\mathbf{x} + \mathbf{v} \cdot \Delta t)\| \\ + \beta \cdot \sum_{o \in O} \left(-\frac{1}{2} \tanh\left(k \cdot (A - d_{\text{safe}})\right) + \frac{1}{2} \right) \end{aligned} \tag{5}$$

where $A = \|\mathbf{x}_o - \mathbf{x}'\|$, $\mathbf{x}$ denotes the current position of the robot, $\mathbf{g}$ denotes the goal of the robot, $\mathbf{v}$ denotes the candidate velocity, and Δt denotes the time step. The predicted position is given by $\mathbf{x}' = \mathbf{x} + \mathbf{v} \cdot \Delta t$, The set O contains all obstacles, each located at $\mathbf{x}_o$. Parameters d_{safe} and k control the shape of the penalty from being close to the obstacle, whereas α and β respectively determine the relative weights of the goal-seeking and obstacle avoidance terms.

The particle with the lowest cost across all iterations (g_{best}) is selected as the robot's next velocity command.

The implementation of this algorithm is summarized in the pseudocode shown in Alg. 1.

Algorithm 1: BB-PSO for Velocity Selection.

```
Initialize particles {v_1, ..., v_n} ← RAV;
Set pbest_i ← v_i, and evaluate J(pbest_i);
Set global best gbest ← arg min_i J(pbest_i);
for k = 1 to N do
    for each particle i do
        Compute μ ← 0.5(pbest_i + gbest);
        Compute σ ← ‖pbest_i − gbest‖;
        Sample new position v'_i ~ N(μ, σ);
        if v'_i is valid (within RAV) then
            Update particle: v_i ← v'_i;
        end
        Evaluate J(v_i);
        if J(v_i) < J(pbest_i) then
            Update personal best:
            pbest_i ← v_i;
        end
    end
    Update global best
    gbest ← arg min_i J(pbest_i);
end
return gbest as the optimal velocity v*
```

2.4 Integration of RVO and PSO

To integrate VO constraints into the BB-PSO framework—and, more importantly, to account for the influence of robot priorities on the optimization—we adopted the following procedure. At each planning step, robot R_A computes the set of RAV, which is defined as the subset of dynamically feasible velocities that do not fall inside any VO generated by other agents. This set serves as the search domain for the BB-PSO algorithm. Particles outside the RAV are rejected, and their positions will not be updated.

Each robot is assigned a scalar priority value, P_i, where a higher value indicates greater importance. Priorities do not alter the VO constraints directly, but they modulate the weights in the cost function to encourage differentiated behavior.

Specifically, the weights α and β in the cost function are adjusted using Eqs. 6.

$$\begin{aligned} \alpha_i &= max(\alpha P_i, 0.1) \\ \beta_i &= max(\beta(1 - P_i), 1.0) \end{aligned} \tag{6}$$

A high-priority robot ($P_i \to 1$) emphasizes reaching a goal and reduces obstacle avoidance penalties.

A low-priority robot ($P_i \to 0$) becomes more conservative, placing greater weight on obstacle avoidance.

We ensured that the obstacle avoidance weight did not fall below the minimum threshold of 1.0. This helps to prevent agents with the highest priority from taking too many risks by ignoring other

agents, possibly causing collisions in clustered environments. Simultaneously, we ensured that the goal-seeking weight was never below 0.1. This ensures that even if the agent has the lowest priority, it will still try to reach its goal.

3 IMPLEMENTATION

3.1 Simulation Setup

To evaluate the proposed approach, we developed a series of simulations in a controlled 2D environment using custom-built tools and clearly defined robot configurations. The simulation was developed in Python and executed using a fixed time-step of $dt = 0.1$ s. The environment comprises a bounded two-dimensional (2D) workspace with multiple holonomic robots. All motion-planning logic, including VO construction and BB-PSO, was implemented from scratch using NumPy for numerical operations and Matplotlib for visualization.

The simulation loop is synchronous; however, the system is nondeterministic owing to the stochastic sampling in BB-PSO. Specifically, new particle positions are sampled from a normal distribution, making the outcome of each run sensitive to random initialization and updates.

Each robot is modeled as a circular agent with a radius $r = 0.3$ m, capable of holonomic motion. The robots are constrained by a maximum speed of $v_{max} = 0.7$ m/s and a maximum acceleration of $a_{max} = 2.0$ m/s². These parameters are based on a robot that will be used for further testing (Hiwonder, 2025).

The robots are initialized with predefined initial positions and static goal locations, allowing a consistent running configuration. Each robot was assigned a fixed priority level that was manually specified at the beginning of each simulation. These values influence the cost function used in the optimization phase. Higher-priority robots seek faster and direct paths to their goals, while lower-priority robots seek safer collision avoidance paths.

3.2 Algorithm Implementation

The algorithm integrates RVO constraints with BB-PSO optimization to compute collision-free velocities in a decentralized multi-robot setting. Each robot iteratively evaluates its reachable velocity space, filters it based on dynamic constraints and collision avoidance conditions, and then applies the BB-PSO to select the most suitable velocity. This process is repeated at each time step until all robots converge to their respective goals within a specified tolerance. The steps in this loop are summarized in the pseudocode shown in Alg. 2. For simplicity, the pseudocode updates the velocities and positions of the robots within the same loop. However, it is important to note that in the actual simulation, these updates are applied only after all robots have independently computed their next velocity. This ensures that each robot makes its decision without access to the updated actions of the others, preserving simultaneity in decision-making.

Algorithm 2: RVO with BB-PSO Optimization.

```
while distance to goal > threshold do
    for R_i in Robots do
        Compute the reciprocal velocity
          obstacle of R_i
        Calculate the reachable velocities of
          R_i
        Filter reachable avoidance velocities
          of R_i
        Optimize RAV with BB-PSO to get
          the best velocity of R_i(t+1)
        Update the velocity of R_i
        Update the position of R_i
    end
end
```

The simulation used an object-oriented approach centered on a *Robot* class, encapsulating all relevant information and methods required for motion planning. Each robot instance stores its current position, velocity, goal, radius, dynamic limits, priority, and internal buffers for storing RVO and RAV. The class also includes methods for updating positions, computing the VO geometry, and filtering velocities based on collision constraints.

This modular design allows each robot to operate autonomously in the simulation loop, thereby enabling straightforward scaling to a larger number of agents. Although the current implementation is single-threaded, the independence of the agents allows parallelization in further research.

4 RESULTS

4.1 Experiment Setup

A two-phase experimental strategy was employed to evaluate the performance of the proposed motion planning algorithm.

In the first phase, a baseline scenario was defined

in which four agents were placed at the corners of a square and tasked with exchanging positions diagonally. Two experiments were conducted using this setup. First, a grid search was performed to identify the optimal values of the cost function parameters α and β, assuming equal priorities among agents. Second, a set of evaluations was conducted under varying priority configurations, using the previously selected parameters that balanced both efficiency and safety. The same priority scenarios were also tested using a greedy approach instead of BB-PSO, to enable a fair performance comparison.

Table 1: Top 5 configurations by mean arrival time.

α	β	Arrival time [s]	Collision Number
5.0	2.0	15.67 ± 1.61	10.6
5.0	1.0	15.73 ± 0.85	6.4
4.0	1.0	16.52 ± 0.63	1.8
4.0	**2.0**	$\mathbf{16.56 \pm 0.23}$	**0.0**
3.0	2.0	16.63 ± 0.68	2.2

The second phase involved testing the algorithm in random scenarios, where both initial and goal positions were sampled randomly to assess the robustness of the approach under varying conditions.

Each individual experiment was repeated five times to account for the stochastic nature of the optimization process, as BB-PSO relies on sampling from Gaussian distributions.

The average performance was evaluated using three metrics: the total travel time, the total travel distance, and the number of collisions observed. Collisions were evaluated at every time step to detect overlaps between robots. As a result, a single collision event could be counted multiple times if the robots remained in contact across consecutive time steps.

The results of these experiments are presented in the next section.

4.2 Parameter Tuning and Weight Selection

To tune the cost function parameters, 25 experiments were conducted by performing a grid search over $\alpha, \beta \in \{1,2,3,4,5\}$, resulting in 5×5 combinations.

Table 1 presents the top five parameter configurations with the lowest mean arrival times.

4.3 Evaluation Under Priority-Driven Scenarios

After completing the grid search over α and β, configurations $\alpha = 4$ and $\beta = 2$ were selected for further evaluation under varying priority assignments. Although this combination did not yield the lowest average arrival time, it consistently demonstrated competitive performance with zero collisions. Therefore, the selected configuration provided a balanced trade-off between speed and safety.

Table 2: Priority configuration for each scenario (Robot 0–3).

Robot	Sc.0	Sc.1	Sc.2	Sc.3	Sc.4	Sc.5	Sc.6	Sc.7	Sc.8	Sc.9
P_0	1.00	1.00	0.25	1.00	0.50	1.00	0.80	0.20	1.00	0.30
P_1	1.00	0.75	0.50	1.00	0.50	0.00	0.60	0.40	0.30	1.00
P_2	1.00	0.50	0.75	0.50	0.50	1.00	0.40	0.60	0.30	0.30
P_3	1.00	0.25	1.00	0.50	0.50	0.00	0.20	0.80	0.30	0.30

To evaluate the impact of priority levels on multi-robot behavior, ten custom scenarios were tested using the selected configurations. In each scenario, the four robots were assigned different static priority values ranging from 0.0 to 1.0, as shown in Table 2.

Figure 1 presents the trade-off between the average arrival time and average distance traveled for all scenarios. Each point is colored according to the average priority assigned to all the agents in that scenario. A general trend was observed: scenarios with higher average priorities (darker red points) resulted in shorter travel distances and shorter completion times. In contrast, scenarios with lower average priorities or greater imbalance tend to show increased path lengths and delays, often owing to more conservative behavior or yielding to high-priority agents.

Almost half of the scenarios resulted in full task completion without any collisions. In contrast, the first scenario—where all robots had maximum priority—exhibited the highest number of collisions, but also achieved the fastest arrival times and the shortest distances traveled. On average, only one collision occurred per scenario, highlighting the overall feasibility and efficiency of the proposed method.

Table 3 presents a summary of the quantitative results for the ten evaluated priority scenarios, including the average arrival time, distance traveled, and num-

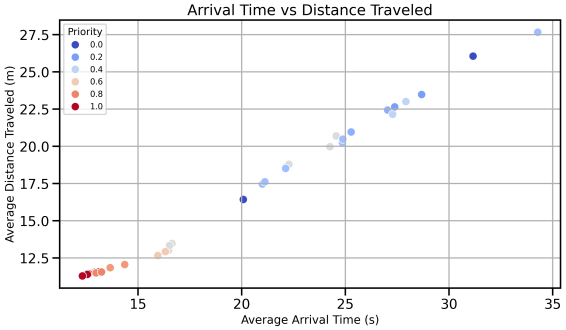


Figure 1: Trade-off between average arrival time and distance traveled for each scenario. Color indicates the average priority value across all four robots.

ber of collisions recorded across simulation runs.

On the other hand, Table 4 presents the results of running the same set of experiments using a greedy approach instead of BB-PSO for the velocity optimization phase. Although the greedy method achieved better average results in terms of arrival time and distance traveled, it resulted in a significantly higher number of collisions, with an average of 6.6 per scenario. This suggests that BB-PSO was able to explore more diverse solutions beyond those initially included in the RAV set. While the proposed method prioritized safety, the greedy strategy led to more aggressive decisions in pursuit of goal completion.

Table 3: Average performance metrics for each scenario using BB-PSO.

Scenario	Arrival Time (s)	Distance (m)	Collisions (avg.)
0	**12.82**	**11.50**	3.0
1	18.80	16.07	0.6
2	19.10	16.10	2.6
3	18.02	15.60	1.0
4	16.53	13.21	**0.0**
5	19.24	16.37	0.6
6	20.99	17.31	**0.0**
7	21.45	17.68	**0.0**
8	20.14	16.91	2.2
9	23.15	19.26	**0.0**
Average	19.02	16.00	1.0

Table 4: Average performance metrics for each scenario using the greedy approach.

Scenario	Arrival Time (s)	Distance (m)	Collisions (avg.)
0	**14.80**	**12.03**	10.0
1	17.03	14.07	19.0
2	19.20	16.19	**0.0**
3	17.38	14.56	2.0
4	18.40	13.93	4.0
5	20.20	16.66	1.0
6	17.55	14.42	18.0
7	21.65	17.19	4.0
8	21.95	17.73	**0.0**
9	17.30	13.77	8.0
Average	18.55	15.06	6.6

4.4 Evaluation with Random Initial Positions and Goals

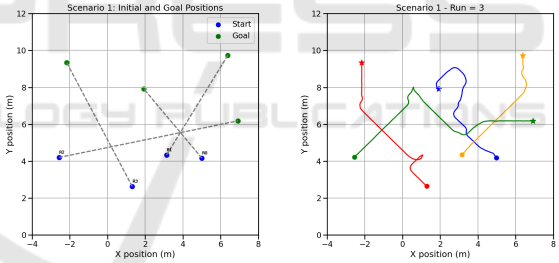
To evaluate the performance of the proposed method under varying conditions, five additional experiments were conducted using randomly assigned initial positions and goals, with all agents assigned the same priority value of 0.5.

The positions were generated under two constraints: each agent's path had to be at least 3 meters long, and both initial and goal positions were placed to prevent overlaps that could lead to collisions at the start or upon arrival.

Table 5: Average performance metrics for scenarios with random positions and goals.

Scenario	Arrival Time (s)	Distance (m)	Collisions (avg.)
0	**5.67**	**4.58**	**0.0**
1	10.66	8.81	2.0
2	7.55	6.28	**0.0**
3	7.28	5.57	**0.0**
4	9.31	7.42	**0.0**
Average	8.09	6.53	0.4

Figure 2 illustrates one of the randomly generated scenarios, along with the trajectories followed by the agents to reach their respective goals. Table 5 summarizes the average performance across multiple runs. Almost all experiments resulted in zero collisions, except for Scenario 1—the case shown in the figure. In this particular instance, several path intersections likely contributed to the observed collisions. Despite this, the results demonstrate that the proposed method is robust across diverse scenarios, consistently maintaining a low collision rate and successfully generating feasible solutions under varying configurations.



(a) (b)

Figure 2: Random Scenario 1. (a) shows the initial and goal positions of the robots, and (b) shows the resulting trajectories.

5 CONCLUSIONS

The proposed methodology, which integrates Reciprocal Velocity Obstacles (RVO) with Bare Bones Particle Swarm Optimization (BB-PSO), effectively facilitates collision avoidance and path planning in multi-robot systems. The incorporation of priority levels into the cost function significantly influences the robot's behavior, enabling differentiated actions based on the assigned importance. A balance between goal-seeking and obstacle avoidance was achieved with the selected weight configuration ($\alpha = 4$, $\beta = 2$), allowing high-priority agents to move more directly

while ensuring overall group safety. Scenarios characterized by higher average priorities generally resulted in shorter travel distances and faster completion times, whereas those with lower or imbalanced priorities exhibited more conservative behavior and potential delays. Certain priority configurations (e.g., scenarios 4, 6, 7, and 9) achieved complete task fulfillment without any collisions, demonstrating the potential for optimized multi-robot coordination using this approach. These findings suggest that the proposed method offers a promising strategy for prioritized motion planning in multi-robot systems, balancing efficiency and safety based on assigned task importance. Future research directions include an in-depth evaluation of BB-PSO against a broader set of optimization algorithms, given that the greedy strategy was less effective in minimizing collisions. Additionally, exploring methods for dynamically adjusting robot priorities based on real-time performance metrics or changing mission objectives, along with extending the model to incorporate task parameterizations, could enhance robot autonomy.

ACKNOWLEDGEMENTS

This research was supported in part by the University of Alberta-Tecnologico de Monterrey Seed Grant Program, under project "Intelligent Distributed Controls for Multi-Agent Autonomous Systems for Safe Interaction with Humans".

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