Computing Science

CS4048 Multi-Robot Autonomous Fossil Discovery System

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CS4048 Report

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1 Introduction

Palaeontological exploration faces significant challenges in remote environments, where manual fossil discovery and collection are time-consuming and resource-intensive. This project implements an autonomous multi-robot system using ROS2 Jazzy Jalisco [2] that coordinates explorer and collector robots to efficiently discover and retrieve fossils. The implementation leverages pyrobosim [1] for simulation, demonstrating key robotics capabilities through two specialized robots: an explorer utilizing a novel multi-mode exploration strategy with occupancy grid mapping, and a collector employing state-based task execution.

The system showcases integration of multiple Computing Science disciplines including distributed systems for inter-robot communication [3], real-time processing for sensor management [4], and advanced algorithms for path planning [5]. Our implementation demonstrates coordinated exploration, robust obstacle avoidance, multi-robot task execution, and sophisticated battery management through predictive path planning.

2 System Architecture

Our system implements a distributed architecture centred on two autonomous robots coordinating through ROS2's publish/subscribe messaging system [8, 6]. The explorer robot publishes fossil discoveries using a structured JSON string as a message, that enables robust inter-robot communication:

```
def publish_fossil_object(self, loc: Location):
    msg = String()
    data = {
        "name": "fossil" + loc.name[-1:],
    }
    msg.data = json.dumps(data)
    self.fossil_discovery_pub.publish(msg)
```

This decoupled design allows the collector robot to asynchronously respond to discoveries while maintaining its own task queue through an efficient callback system.

2.1 Resource Management

The system implements sophisticated resource management through the ChargingCoordinator class [3], which handles distributed access to charging stations:

```
class ChargingCoordinator:
    def __init__(self):
        # Maps charger names to robot names
        self.charging_stations: Dict[str, str] = {}
        # Maps charger names to reserved robot names
        self.reservations: Dict[str, str] = {}
```

When a robot's battery level falls below the safe threshold, it queries the coordinator for the nearest available charging station, which then assigns the station to the robot. The explorer makes use of this mechanism which could be extended to the collector to prevent both robots from charging at the same station.

2.2 Component Integration

The system's components are integrated through the WorldROSWrapper class [1], which provides the core infrastructure for robot interaction. The environment mapping system utilises a sophisticated three-state occupancy grid where each cell maintains temporal metadata for exploration efficiency [9]. This shared world model enables both robots to maintain consistent environmental understanding while operating independently.

The collector robot implements a state-based task execution system that synchronises with the explorer's discoveries. When a fossil is discovered, the collector evaluates its current state, battery level, and task queue to determine the optimal collection strategy. This coordination is achieved through a robust error handling system that manages path replanning, charging station access, and failed collection attempts.

The integration architecture emphasises fault tolerance through comprehensive error recovery mechanisms. Path execution failures trigger dynamic replanning, while battery management failures initiate emergency charging protocols. This layered approach to error handling ensures system stability even in challenging scenarios.

3 Explorer Implementation

The explorer robot's implementation centres on sophisticated environmental mapping and intelligent exploration strategies [9], implemented through the ExplorationGrid class. This system maintains a probabilistic representation of the environment while ensuring efficient coverage through temporal tracking and adaptive exploration modes.

3.1 Environmental Mapping System

The environment is discretised into a grid where each cell $c_{i,j}$ maintains both occupancy and temporal information [3]. The occupancy system employs a novel three-state approach:

$$c_{i,j} = \begin{cases} -1 & \text{unknown space} \\ 0 & \text{confirmed open space} \\ 1 & \text{detected obstacle} \end{cases}$$

Each cell additionally maintains temporal metadata $\tau_{i,j} = (v_{i,j}, t_{i,j})$, where $v_{i,j}$ represents visit count and $t_{i,j}$ the last visit timestamp. This temporal data enables the calculation of local coverage density $D(x,y)$:

$$D(x,y) = \frac{\sum_{(i,j)\in N(x,y)} v_{i,j}}{|N(x,y)|} \cdot \exp(-\alpha(t_{\text{current}} - t_{i,j}))$$

where $N(x,y)$ represents the neighbourhood cells and α is a temporal decay factor.

3.2 Multi-Mode Exploration Strategy

The exploration system dynamically switches between three complementary strategies based on environmental conditions and coverage metrics [5]:

Spiral Exploration

The primary exploration phase employs an Archimedean spiral defined by:

$$r = a + b\theta$$
$$x = r\cos(\theta) + x_0$$
$$y = r\sin(\theta) + y_0$$

where the step size b adapts to local obstacle density ρ_{obs}:

```
def get_spiral_target(self, current_x, current_y):
    self.spiral_params["radius"] += self.spiral_params["step"]
    self.spiral_params["angle"] += math.pi / 8
    next_x = current_x + self.spiral_params["radius"] *
             math.cos(self.spiral_params["angle"])
    next_y = current_y + self.spiral_params["radius"] *
             math.sin(self.spiral_params["angle"])
```

Obstacle Detection and Processing

The system implements a sophisticated object detection system combining ray-casting with probabilistic modelling [4]. For a given robot pose $p = (x, y, \theta)$, the detection algorithm projects n rays (default: 64) at uniform angular intervals. Each ray r_i is processed using the Bresenham line algorithm for efficient collision detection:

```
def check_for_objects(self, robot_pose, detection_params={
    "radius": 3.0,
    "min_probability": 0.3,
    "n_rays": 64,
    "scan_interval": 0.2,
}):
    scan_points = []
    for radius in np.arange(0, detection_params["radius"],
                            detection_params["scan_interval"]):
        angles = np.linspace(0, 2 * np.pi,
                             detection_params["n_rays"])
        for angle in angles:
            x = robot_pose.x + radius * np.cos(angle)
            y = robot_pose.y + radius * np.sin(angle)
            scan_points.append((x, y))
```

For each detected object, the visibility score V is calculated as:

$$V(d) = (1 - \frac{d}{d_{\max}}) \cdot \prod_{i=1}^{n} v_i$$

where d is the distance to the object, $d_{\max}$ is the maximum detection range, and v_i represents individual ray visibility values.

Line of Sight and Obstacle Processing

The line of sight calculation is critical for both navigation and object detection. For each potential obstacle, the system performs geometric intersection tests:

```
def check_line_of_sight(self, start_x, start_y, end_x, end_y,
                        obstacles):
    for obstacle in obstacles:
        if obstacle.category not in ["rock", "bush"]:
            continue

        line = LineString([(start_x, start_y), (end_x, end_y)])

        if hasattr(obstacle, "polygon") and
           obstacle.polygon.intersects(line):
            return False

        if hasattr(obstacle, "pose"):
            obstacle_point = Point(obstacle.pose.x,
                                   obstacle.pose.y)
            if line.distance(obstacle_point) < 0.6:
                return False
    return True
```

Different obstacle types have specific safety margins: - Rocks: 1.25 unit safety margin with rigid boundary modelling - Bushes: 0.6 unit safety margin with soft boundary properties - Fossils: Specialized detection parameters for small object identification

3.3 Error Recovery and Path Optimisation

The system implements a comprehensive error recovery framework triggered by the stuck detection system [7]. When progress is impeded (stuck_count $\geq$ MAX_STUCK_COUNT), the system employs a gradient descent approach to find alternative paths:

$$p_{\text{escape}} = \text{argmin}_{p \in P_{\text{candidates}}} \sum_{o \in O} w_o \cdot d(p, o)$$

where $P_{\text{candidates}}$ represents potential escape positions, O is the set of detected obstacles, and w_o are obstacle-specific weights.

The implementation includes adaptive replanning:

```
def get_unstuck_position(self, current_pose, search_radius=2.0,
                         increments=8):
    for radius in np.arange(0.5, search_radius, 0.5):
        for angle in np.linspace(0, 2 * np.pi, increments):
            test_x = current_pose.x + radius * math.cos(angle)
            test_y = current_pose.y + radius * math.sin(angle)
            if self.exploration_grid.is_valid_point(test_x, test_y) and
                self.exploration_grid.is_path_clear(
                    current_pose.x, current_pose.y, test_x, test_y):
                return test_x, test_y
```

This comprehensive system ensures robust exploration while maintaining efficient coverage and reliable object detection. The integration of multiple exploration strategies with sophisticated error recovery mechanisms enables effective operation in complex, unknown environments.

4 Collector Implementation

The collector robot implements a state-based task execution system [6] that handles fossil collection operations while maintaining energy efficiency through predictive path planning. The implementation extends the WorldROSWrapper class [1], incorporating both ROS2's topic-based communication and pyrobosim's object manipulation capabilities.

4.1 Task Execution Framework

The collector's core task execution system revolves around a queue-based architecture that processes fossil discoveries asynchronously [8] as the explorer reports them through the aforementioned `fossil_discoveries` topic. The task execution incorporates energy-aware path planning through the `go_to_pose_through_charger` method, which navigates the robot directly to the goal, or through the most optimal charger considering the goal position; choosing the charger that minimises the added path length, thus energy usage:

$$E_{start,goal} = \min_{c \in C}(E_{start,c} + E_{c,goal})$$

where $E_{A,B}$ represents the energy cost of the direct path from A to B avoiding obstacles, and C represents the set of all chargers on the map.

4.2 State Machine Design

The collector implements a hierarchical state machine [3] that manages collection operations through distinct states:

1. *Idle*: Base state, processing discovery messages
2. *Navigation*: Moving to target location (fossil or base) with energy awareness
3. *Collection*: Executing pickup operation
4. *Placement*: Executing place operation to deposit fossil at base
5. *Charging*: Managing battery levels

State transitions are governed by both internal conditions and external events:

```
def base_station_behaviour(self):
    robot = self.get_robot()
    if self.is_at_base() and robot.manipulated_object is not None:
        robot.place_object()
        self.collection_queue.pop(0)
        if len(self.collection_queue) > 0:
            g = self.get_pickup_pose_for_object(self.collection_queue[0])
            self.go_to_pose_through_charger(g)
```

4.3 Path Finding

The collector robot uses pyrobosim's built-in Rapidly-exploring Random Tree Planner (RRT-Planner) for pathfinding. This relies on pyrobosim's Pose and Path objects which are incorporated into our collection execution system.

4.4 Object Manipulation

The object manipulation system integrates with pyrobosim's navigation framework through a series of carefully coordinated operations [4]. For fossil collection, the system first validates the approach pose. This is necessary as interacting with objects is only possible if the robot is at one of the predefined `nav_poses` of the object's location:

```
def get_pickup_pose_for_object(self, fossil_obj_name):
    fossil_obj: Object = self.world.get_object_by_name(fossil_obj_name)
    spawn: ObjectSpawn = fossil_obj.parent
    return self.get_nearest_pose(spawn.nav_poses)
```

5 Energy Management

The system implements a sophisticated energy management framework [3] that coordinates charging access between robots while optimising path planning for energy efficiency. The implementation spans three interconnected components: a core battery model, a distributed charging coordinator, and a specialised explorer battery manager.

5.1 Energy Model

The battery system models energy consumption through a composite function that accounts for different motion types:

$$E_{total} = E_{linear} + E_{angular} + E_{actions}$$
$$E_{linear} = d_{linear} \cdot k_{move}$$
$$E_{angular} = \theta_{rotation} \cdot k_{rotate}$$

where k_{move} and k_{rotate} are robot-specific constants (2.0 units/distance for collector, 1.0 for explorer). This is implemented through a drain calculation system:

```
def get_drain_for_path(self, path: Path) -> float:
    drain = 0.0
    for i in range(path.num_poses - 1):
        current_pose = path.poses[i]
        next_pose = path.poses[i + 1]
        linear_drain = (current_pose.get_linear_distance(next_pose)
                         * self.drainPerDistanceUnit)
        angular_drain = abs(current_pose.get_angular_distance(next_pose)
                             * self.drainPerRadianRotate)
        drain += linear_drain + angular_drain
    return drain
```

5.2 Distributed Charging Coordination

The explorer's battery manager implements a charging coordination protocol [6] that optimises charging station selection while the collector implements direct charging access:

```
def get_best_available_charger(self, start: Pose, world: World,
                               planner: RRTPlanner, goal: Pose = None):
    chargers = world.get_locations(["charger"])
    path_length = None
    best_charger = None

    for charger in chargers:
        if not self.is_charger_available(charger.name):
            continue

        for docking_pose in charger.nav_poses:
            plan_to_charger = planner.plan(start, docking_pose)
            if plan_to_charger is None:
                continue

            length = (plan_to_charger.length +
                      planner.plan(docking_pose, goal).length
                      if goal else plan_to_charger.length)

            if path_length is None or length < path_length:
                path_length = length
                best_charger = charger
```

The explorer's charging strategy optimizes station selection based on:

$$C_{\text{optimal}} = \text{argmin}\, c \in C_E(d(p\text{current}, p_c) + d(p_c, p_{\text{goal}}))$$

where C_E is the set of charging stations available to the explorer, and $d(\cdot,\cdot)$ represents the path distance function. The collector robot implements a simpler direct charging strategy, engaging charging functions when at any charging station location.

5.3 Predictive Energy Management

Both robots implement predictive energy management through path validation [5]:

```
def is_safe_path(self, path: Path) -> bool:
    goal_pose = path.poses[-1]
    path_to_charger, _ = self.battery.get_optimal_charger(
        goal_pose, self.world, self.robot.path_planner)
    drain_path = self.battery.get_drain_for_path(path)
    drain_charger_path = self.battery.get_drain_for_path(path_to_charger)
    return self.battery.charge >= drain_path + drain_charger_path
```

This ensures sufficient energy remains for both task completion and emergency charging by maintaining the invariant:

$$E_{current} \geq E_{task} + \min_{c \in C} E_{to\_charger}(c)$$

The integration of these three components enables sophisticated energy management while maintaining system stability through distributed coordination and predictive planning.

6 Technical Analysis & CS Integration

Our implementation integrates multiple Computing Science disciplines, each contributing to system robustness while maintaining real-time performance guarantees. Here we analyse the key algorithmic complexities and system properties.

6.1 Algorithmic Complexity

The exploration system's computational complexity is dominated by three key operations:

$$\begin{aligned} T\text{total} &= T\text{exploration} + T\text{detection} + T\text{planning} \\ T\text{exploration} &\in O(n \log n) \text{ for grid updates} \\ T\text{detection} &\in O(kr) \text{ for } k \text{ rays and } r \text{ objects} \\ T_{\text{planning}} &\in O(n^2) \text{ for RRT optimization} \end{aligned}$$

The ray-casting implementation in `check_for_objects` optimizes sensor processing through spatial indexing:

```
def check_for_objects(self, robot_pose, detection_params):
    fossil_sites = [loc for loc in self.world.locations
                    if loc.category == "fossil_site_box"]
    static_obstacles = [loc for loc in self.world.locations
                        if loc.category in ["rock", "bush"]]
```

6.2 Real-Time Guarantees

The system maintains real-time responsiveness through several mechanisms: 1. Distributed State Management: - Explorer updates: 10Hz for sensor processing - Collector updates: 2Hz for task execution - Battery monitoring: 1Hz for energy tracking 2. Message Passing Performance:

```
def fossil_discovery_callback(self, msg):
    try:
        data = json.loads(msg.data)
        if data["name"]:
            fossil_obj_name = data["name"]
            if len(self.collection_queue) == 0:
                g = self.get_pickup_pose_for_object(fossil_obj_name)
```

6.3 System Robustness

The implementation achieves robustness through layered error handling and resource management:

Explorer Energy Management: The charging coordinator implements a reservation system for the explorer robot:

$$\forall r \in Explorers : \exists c \in Chargers : (r \to c) \land \neg(\exists r' \neq r : r' \to c)$$

Resource Management: Both robots ensure energy availability through predictive modelling:

$$E_{success} \iff E_{current} \geq E_{path} + min_{c \in Chargers}(E_{to\_charger}(c))$$

This integration of Computing Science principles enables reliable autonomous operation while maintaining system stability and real-time responsiveness.

7 Conclusion

Our implementation successfully demonstrates an autonomous multi-robot system for fossil discovery and collection [3], integrating sophisticated exploration strategies with robust energy management. The system's key innovations include a dynamic multi-mode exploration system [5], distributed charging coordination, and probabilistic object detection [9]. Through the integration of Computing Science principles—from distributed systems to real-time processing—we've created a reliable framework for autonomous exploration. While currently limited by pyrobosim's [1] 2D environment, future work could extend to 3D simulation in Gazebo [8], implement multi-sensor fusion for improved object detection, and incorporate machine learning for enhanced fossil classification.

Word Count: 1416

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