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ADVANCED SOLUTONS AND CHALLENGES IN MULTI-DRONE SYSTEMS FOR SEARCH AND RESCUE MISSIONS: TECHNICAL APPROACHES AND UNRESOLVED MATTER

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Abstract

This paper provides an overview of the literature on the development of a heterogeneous multi-drone system for search and rescue missions as part of the project "CHeMSys: Cooperative Heterogeneous Multi-drone System for disaster prevention and first response". Several types of scenarios will be addressed, taking into account ground, water and air vehicles. The focus is on analysing the latest findings on unresolved technical challenges in this area.

Keywords: Cooperative Control, Multi-Drone System, Search and Rescue, Fault Detection and Isolation

1. General Introduction

In recent decades, the number of natural disasters that cause irreversible damage to both the environment and human communities has increased significantly. Examples of such disasters include earthquakes, floods, fires and tsunamis, all of which pose a threat to human safety and hinder the implementation of dangerous rescue operations. It is impossible to avoid such events and the definition of an effective disaster management system is therefore essential. To improve its effectiveness, such a system must have comprehensive information about the people affected by the disaster and precise details about the location and nature of the event. This information is invaluable for decision-making and the organization of first aid teams.

In another context, robots have proven to be indispensable tools in operations that are considered Dull, Dirty and Dangerous. This is mainly due to their ability to reach dangerous or inaccessible places for humans, such as toxic or extremely hot environments, thus increasing the safety of rescue teams and operational efficiency.

In addition, rapid response within minutes of a disaster is an important goal, and the use of autonomous robotic systems can be critical to this goal.

The first use of robots in an urban search and rescue (USAR) operation dates back to September 2001 during the 9/ 11 attacks in New York, USA. Subsequent events such as the La Conchita landslide in 2005, Hurricanes Katrina and Wilma in 2005, the Midas gold mine collapse in 2007, the Fukushima nuclear power plant disaster in 2011 and the Tohoku earthquake in 2011 witnessed the use of robots in search and rescue operations. Despite the increasing importance of robotic systems in the disaster response phases, their deployment usually occurs about 6.5 days after the disaster, exceeding the 48-hour peak of the mortality curve, as reported by [1]. The delay can be attributed to various factors, including technical challenges. The predominant mode of operation for these robotic systems is remote control, which requires a high level of expertise and specialized training for human operators. As a result, only a few specialists are able to operate these robotic systems, which significantly limits their potential applications.

Several bottlenecks further limit the use of robotic systems in disaster relief. These include the limited reliability and autonomy in terms of intelligence, energy and mobility of robots, insufficient integration

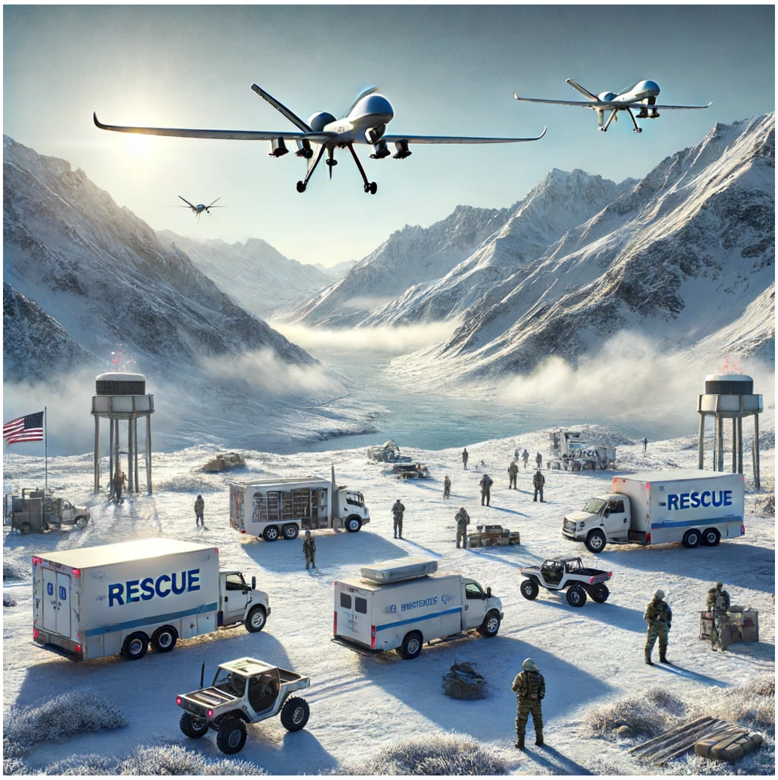

Figure 1 – Terrestrial scenario.

with rescue coordination centers and inadequate coordination between the robotic units deployed during an operation.
This paper addresses specific technical challenges closely related to the deployment of a multi-robot system (MRS) in complex scenarios:

- Coordinated control of heterogeneous robotic platforms with limited capabilities;
- Techniques for fault detection and isolation.

2. Case Studies of Multi-Robot Systems in Complex Scenarios

Two distinct case studies are considered in order to resume typical challenges in deploying such kind of system. The former is a terrestrial scenario, typical for surveillance or search and rescue missions. The latter is a marine/submarine scenario, typical for inspection and security operations that involve also unmanned surface and underwater vehicles.

2.1 Case Study 1: Terrestrial Scenario - Long-Range Search and Surveillance of Extended Areas

In the terrestrial scenario, as depicted in Fig.1, rescue teams must operate in challenging environments and mantain stable communications with the rescue coordination center. A MRS can significantly aid in overcoming these communication challenges in hostile or inaccessible terrains. Unmanned Ground Vehicles (UGVs) can serve as mobile bases, autonomously navigating difficult terrains to transport necessary tools and supplies for rescue operations. These UGVs enhance logistical support by accessing areas that are difficult for human operators to reach.
Additionally, drones with stationary flight capabilities (RUAVs) provide high-resolution reconnaissance and surveillance, flying over inaccessible areas to offer detailed overviews, detect distress signals, and identify threats. The data collected by RUAVs is transmitted in real-time to the rescue coordination center, facilitating informed decision-making and coordinated rescue efforts. Fixed-wing drones (UAVs) complement this by covering larger areas, providing higher temporal resolution for surveillance and monitoring, and assisting in planning rescue operations.

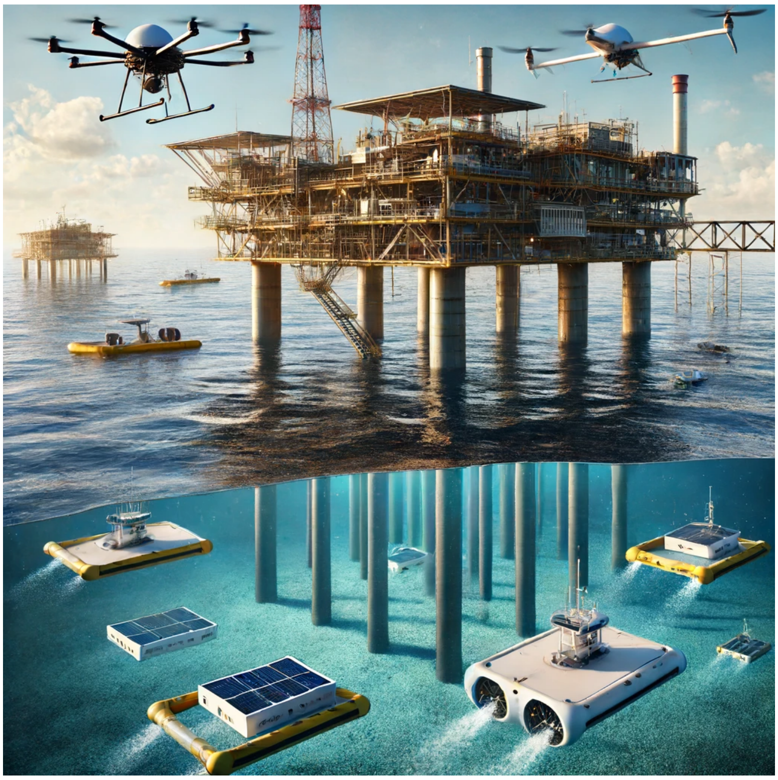

Figure 2 – Marine Scenario.

In scenarios where direct communication between UGVs and the coordination center is unavailable, aerial units can act as communication relays, ensuring constant communication and critical information exchange between field teams and the rescue coordination center. The integration of ground robots and drones in an MRS enhances rescue teams coverage, surveillance, and logistical support, improving coordination, field team safety, and the success rate of rescue operations in inaccessible environments.

2.2 Case Study 2: Marine Scenario - Submarine Intervention for Inspection, Security, and Handling Operations

In the marine scenario illustrated in Fig. 2, an MRS can be invaluable in responding to underwater accidents or environmental disasters, such as ship collisions or pollution spills. Deploying robotic units in such environments mitigates risks to human operators and enhances operational efficiency by allowing robots to perform multiple tasks in parallel.

Unmanned Underwater Vehicles (UUVs) equipped with advanced sensors can detect and map spills, conducting monitoring and sampling to assess their impact on the seafloor and marine life. Other UUVs, equipped with robotic arms or manipulation tools, can perform repair or inspection tasks on damaged sub-sea infrastructures, such as pipelines or cables, by executing welding, cutting, or installing ancillary equipment.

Specialized UUVs can search for and recover lost persons or objects at sea, using high-resolution sonar for precise location and manipulators for recovery operations. The MRS ensures operational resilience, as the failure of one or more robots does not compromise the entire mission. Data collected by the robots facilitates better situational understanding and informed decision-making by rescue teams.

Surface drones act as mobile bases, monitoring the water surface, coordinating underwater operations, and serving as communication links between submarine robots and the rescue coordination center. Equipped with sensors, these drones detect potential threats, report vessel presence, and locate floating victims, providing real-time data transmission and maintaining stable communications. Overall, the use of an MRS in marine scenarios improves the effectiveness, efficiency, and safety of rescue operations, mitigating the consequences of marine disasters or accidents.

3. Outstanding Challenges

Despite the distinct nature of the two operational scenarios, the technical issues they present are quite similar. In both scenarios, the system must define collision-free trajectories for each robotic unit concerning the designated tasks. Simultaneously, each robot must autonomously execute its task while incorporating mission scenario information. The ability of every involved robots to coordinate and cooperate is crucial for developing an efficient and autonomous multi-robot system (MRS).
Reliability is an important feature for a MRS, necessitating self-diagnosis and reconfiguration capabilities that, in real-time, adjust operational strategies to account for variations in the nominal capabilities of each unit. This section addresses two primary unresolved issues, highlighting solutions proposed in the literature.

3.1 Coordinated Control of Heterogeneous Robotic Platforms with Limited Capabilities

Trajectory planning in multi-robot systems (MRS) is a critical research area in autonomous robotics [2, 3, 4, 5, 6]. The objective is to ensure coordinated, safe, and efficient movement of robot groups within complex operational scenarios. This challenge involves addressing several significant problems requiring advanced technical solutions.
The primary challenges in MRS trajectory planning are:

1. **Coordination** - A key difficulty is coordinating the movements of each robot to prevent collisions with each other and environmental obstacles. The planning process must account for dynamic interactions and specific motion constraints of each robot.

2. **Computational Complexity** - Providing real-time solutions necessitates computationally efficient algorithms and methods. As the number of robots increases, the computational complexity grows exponentially, requiring heuristic or optimization-based approaches.

3. **Scalability** - The system's scalability becomes challenging with an increasing number of robots. Effective trajectory planning must manage large fleets without compromising safety or overall efficiency.

Trajectory planning techniques for mobile robots are generally categorized into three main approaches [7]: search-based methods, sampling-based methods, and optimization-based methods.

a) Search-based methods, including the A* algorithm and its variants (e.g., D* and Theta*), consider kinematic constraints and obstacles [8, 9].

b) Sampling-based methods, primarily represented by Rapidly exploring Random Tree (RRT), frame the motion planning problem as a graph search, where nodes represent points in obstacle-free regions, and arcs denote collision-free paths [10, 11, 12].

c) Optimization-based methods treat trajectory planning as a mathematical optimization problem, generating continuous trajectories without an exponential increase in computational complexity [13].

In scenarios with multiple robots, trajectory planning must also address collision avoidance. This is often achieved through reactive control techniques, equipping each robot to react to other robots that obstruct its path. Reactive approaches in the literature include the potential field method [14], the vector field histogram method [15], the curvature-velocity method [16], the dynamic window approach [17], the elastic band method [18], and null-space-based behavioral control [19, 20].
Reactive control strategies have limitations when trajectory changes are not feasible. An alternative strategy decomposes autonomous navigation into path planning and speed profile assignment [21, 22, 23], though this may be unsuitable for missions with strict time constraints.
Coordinated control of robotic movements presents unique algorithmic challenges not encountered with single robots. Each unit must coordinate movements to avoid collisions and optimize overall performance. Despite the increased complexity, MRS offers significant benefits [24, 25, 26, 27].

Effective task coordination necessitates algorithms that synchronize robotic actions and distribute tasks efficiently according to individual robot capabilities [28, 29, 30, 31, 32, 33]. A successful multi-robot coordination algorithm must meet four conditions:

1. Distributed operation, where individual robots act based on their available information.
2. Decentralized execution, ensuring algorithms do not depend on the team size.
3. Safety, allowing robots to avoid collisions with each other and the environment.
4. Emergent properties, where global system properties arise from local interaction rules [34, 35].

Numerous algorithms meeting these criteria have been proposed and successfully utilized for platoon formation [36, 37], area monitoring [38, 39], and border patrolling [40, 41].

3.2 Fault Detection and Isolation Techniques

The effectiveness of MRS in various applications, notably in reducing operational costs and enhancing mission efficiency, is well-recognized [42]. However, reliability issues still constrain the mission types an MRS can accomplish.

Ensuring reliability means these robotic units must withstand potential faults or malfunctions to complete missions or execute contingency operations. In critical mission scenarios, real-time intelligent diagnostic techniques are essential for detecting faults and implementing reconfiguration or contingency strategies. Rapid fault detection and isolation are vital to minimizing the impact on mission completion [43, 44, 45, 46, 47, 29, 48, 49].

A fault is defined as an unacceptable deviation of a system parameter from its desired state [50]. Faults affecting robotic platforms' task performance fall into three main categories [51]:

- **Actuator Fault** - Malfunctions in components of the locomotion/propulsion system impacting robot dynamics (e.g., motor faults).
- **Process Fault** - Internal parameter changes affecting system dynamics (e.g., data transmission delays in remote control).
- **Sensor Fault** - Abnormal deviations in feedback control measurements (e.g., encoder or IMU faults).

Fault detection and isolation (FDI) approaches are broadly classified into model-based and data-driven methods. Model-based methods rely on analytical redundancy [29, 52, 49], using known system behavior to generate fault-sensitive signals (residuals). These methods include parameter estimation, parity equations, state observers, or set-based considerations. Based on residual signals, a decision system detects faults and develops reconfiguration strategies to minimize the fault impact. The primary limitation of model-based FDI schemes is their effectiveness mainly for linear systems. For systems with significant nonlinearities, complex solutions (e.g., Extended Kalman Filter (EKF), particle filters, or nonlinear observers) may be necessary. Implementing real-time fault detection methods can also be challenging for computing units with limited onboard capacity.

Hardware redundancy techniques often provide the most common solution for increasing robotic systems' reliability. However, they have drawbacks, including weight, power consumption, and cost, especially for robots with small payload capabilities. When a reliable mathematical model is unavailable, data-driven approaches can be an alternative, extracting necessary FDI information directly from the system through data manipulation [53]. Recent advances in artificial intelligence (AI) have led to data-driven approaches using neural networks [54, 55], which automatically recognize and learn key system behaviors. Neural network-based replicas exhibit high accuracy and can autonomously detect faults and anomalies, enabling intelligent FDI systems.

From a broad perspective, methods for planning trajectories for mobile robots can be categorized into three primary groups [7]: a) search-based techniques [8, 9], b) sampling-based methods [10, 11], and c) optimization-based methods [13].

In a deployment scenario involving multiple robots, aside from the trajectory planning challenge, the issue of avoiding collisions between the robots must also be addressed. Therefore, their trajectories need to be coordinated [19, 18].
The synchronized control of robotic motions introduces algorithmic challenges that are not encountered when dealing with a single mobile robot. Each unit needs to coordinate its movements effectively to prevent collisions and enhance the overall system performance. Despite the accompanying increase in management and control complexity, the utilization of a Multi-Robot System (MRS) brings about substantial advantages, as highlighted in various studies [24, 25, 26, 27].
The coordination of tasks necessitates the development of algorithms that facilitate both the synchronization of robotic actions and the efficient distribution of operational tasks based on the individual capabilities of the robots. Coordinated control tackles the challenge of optimizing the overall performance of the entire multi-robot system by devising strategies that maximize the efficiency of task execution.
In general, for a multi-robot coordination algorithm to be effective, it must meet four fundamental conditions:

- It must be distributed, allowing individual robots to act solely based on the information available to them, such as through recognition or active communication.
- It must be decentralized, in order to make the algorithms not dependent on the size of the entire team.
- It must ensure safety, enabling robots to avoid collisions with each other and the environment.
- It must exhibit emergent properties, meaning that the global properties of the system must arise from the local interaction rules [34, 35].

Several algorithms that meet these conditions have been proposed in the literature and have proven successful in forming and maintaining formations [36, 37], monitoring areas [38, 39], and patrolling border areas [40, 41].

4. Conclusions

The deployment of autonomous robots for search and rescue (SAR) missions following environmental disasters is becoming increasingly important. This paper examines the current status of multi-robot SAR systems, focusing on two specific scenarios. As part of the PRIN CHeMSys project, this paper addresses fault detection and isolation as well as the planning of coordinated, robust trajectories for MRS units. We have also highlighted the main open research questions and pointed out the remaining challenges. Future work will continue to address theoretical and practical issues related to the implementation of a complete robotic system, with the aim of providing a proof-of-concept.

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6. Copyright Statement

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