A Decentralised Strategy for Heterogeneous AUV Missions

Yaniel Carreno, Èric Pairet, Yvan Petillot and Ron Petrick

Edinburgh Centre for Robotics

Heriot-Watt University & The University of Edinburgh, Edinburgh, UK.

Aim: Improve the quality of multi-robot plans focusing on the optimisation of the goal distribution to enhance long-term autonomy and overall fleet robustness. This is achieved with a new strategy that enhance plan quality through the relaxation of plan search.

Motivation: The increasing demand for multi-platform solutions capable of implementing **long-term missions** more dynamically requires robust **planning** and execution tools which support the operation. Planning offers techniques for managing typical problems that arise in **highly constrained missions**. However, AI planners deal with the high-dimensionality of the state-space inefficiently, leading to multi-robot plans with poor plan quality.

Multi-Vehicle Temporal Planning

Temporal Planning: Automated planning is the process of reasoning about the actions needed to achieve a set of goals. Planning considers the states transitions to model the system. The state transition system is commonly defined as $\sum = (S, A, E, \gamma)$. Here S is the set of possible states, A is the set of possible actions, E is the set of exogenous events, and $\gamma : S \times A \times E$ is the state transition function.

Temporal Planning involves explicit representations of time in the planning problem, allowing more realistic modelling of real-world domains. We evaluate two benchmark temporal planners successfully tested in real underwater missions: Forward-Chaining Partial-Order Planning (**POPF**) and Optimaizing Preferences and TIme-dependent Costs (**OPTIC**).

Underwater Oil Rig Scenario: A segmented environment for modelling multi-robot real-world problems.

Figure 1: *A depiction of the domain which presents the initial position of surface and underwater robots, the docking point (DP) and transmission centre (TC).*

- The planning domain contains tasks associated with multiple sensors.
- Centralised task planner finds a plan for a heterogeneous robots fleet.
- Mission's goals contain: poi exploration, valve-state detection, image or scan data acquisition.
- The domain is defined using Planning Domain Definition Language (**PDDL**) [1].

Methods & Performance Evaluation

Domain Definition: The actions defined in the domain are associated with individual robot capabilities. The constraints influence the set of actions the robot implements. The goals set is a tuple $G := \langle R, RC \rangle$, where R is a set of robots and RC represents the robot's capabilities. The planning problem is a tuple

$$\Pi := \langle P, V, A, I, G, W \rangle. \quad (1)$$

P is a set of Boolean variables, V is a vector of real variables, A is a set of actions which depends of the **domain constraints**, $I(P, V)$ is a function over $P \cup V$ which describes the initial state, $G := \{g_1, ..., g_n\}$ is a set of goals, $W := \{w_1, ..., w_m\}$ is a set of time windows.

Multi-Agent Approach & Architecture: Temporal planning is capable of dealing with multi-agent planning problems since time is modelled explicitly.

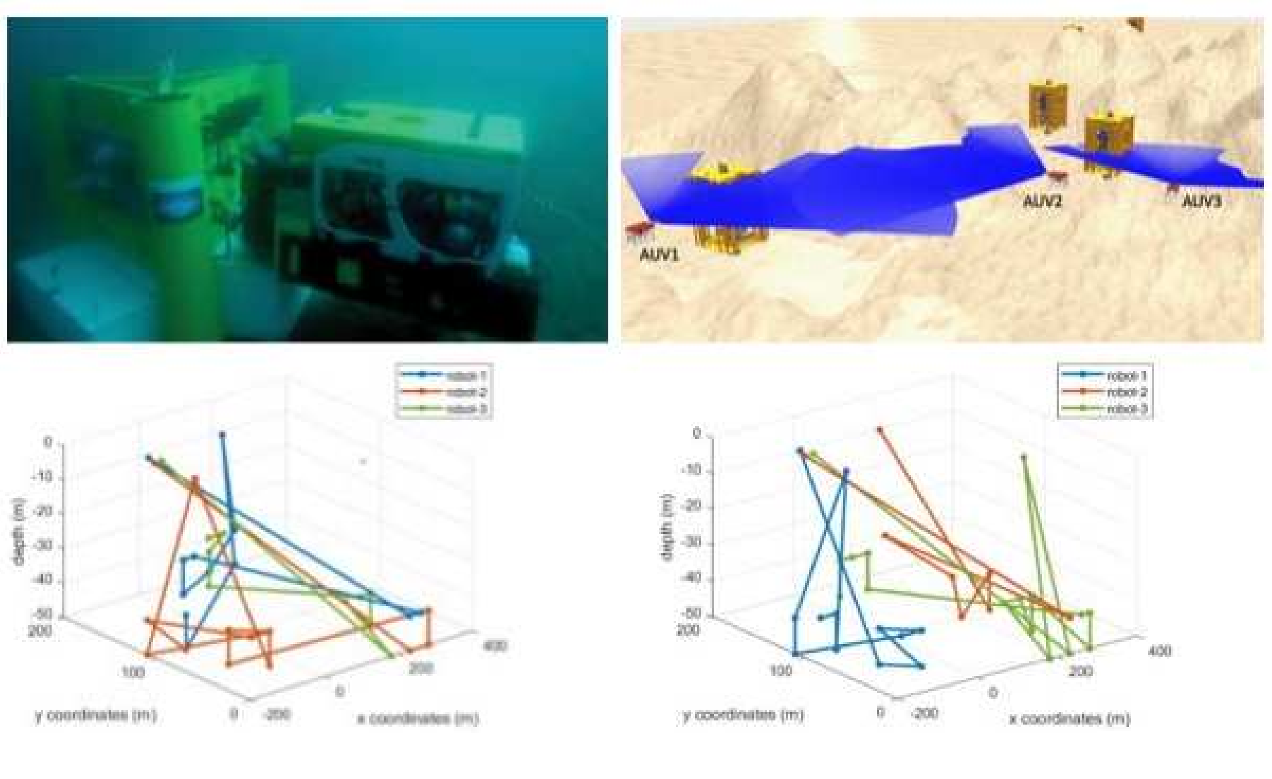

Figure 2: *Benchmark planners, POPF (bottom left) and OPTIC (bottom right), generate non-optimal goal distributions leading to sub-optimal plans for a fleet of three robots.*

We introduce a Goal Allocation (GA) which adds a set of constraints to the PDDL problem to guide the planner's search. GA is based on *k-means* approach to allocate the goal based on their coordinates. **ROSPlan** [2] framework is used to integrate high level task planner and the low level control.

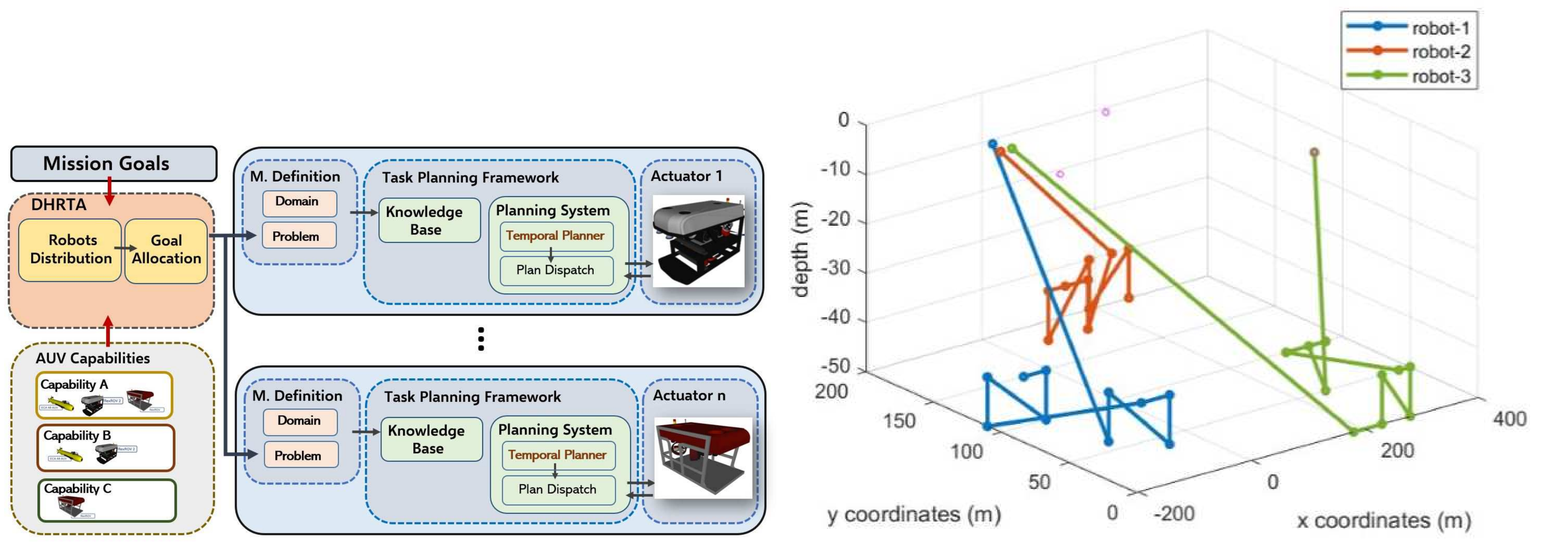

Figure 3: *General system architecture (left) and goal spatial distribution (right) for a fleet of three robots using the GA results to generate the plan.*

The performance analysis considers 6 problems of increasing complexity. We compare the plan quality based on the makespan and planning time results.

- Benchmark planners are sensitive towards changes in numeric constraints.
- For simple problems the GA+TP approach and benchmark TP present similar results.
- For complex missions GA+TP outperforms the benchmark planners due to the relaxation provided by the GA.

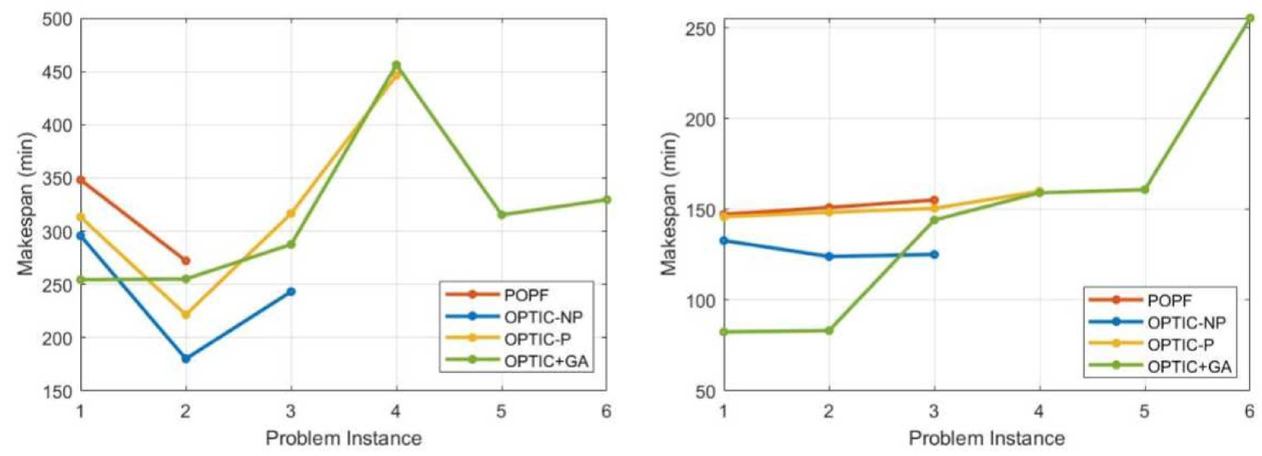

Figure 4: *Plan makespan for a fleet of two robots(left) and three robots (right). The combination of the GA and temporal planning provides a solvable plan for all the problems.*

- GA+TP generates the first solvable plan in shorter time period than benchmark planners (left – 2 robots, right – 3 robots).
- Plan generation time influences the capacity of the robotic system to react optimally during time sensitive tasks.

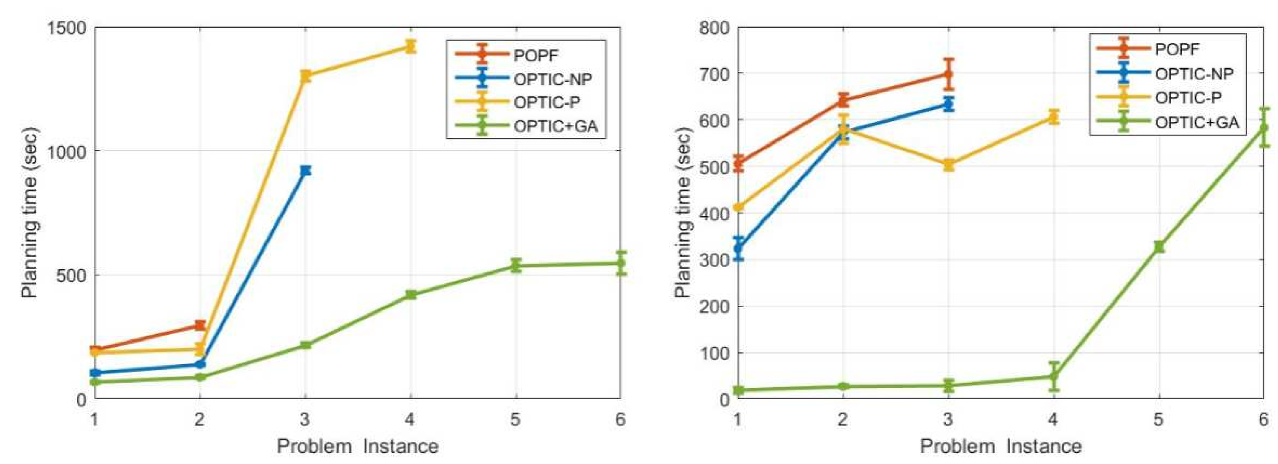

Figure 5: *Planning time results for a fleet of two robots (left) and three (robots) using benchmark planners and GA+TP.*

Conclusions

- Experiments with off-the-shelf temporal planners (POPF, OPTIC) using a comprehensive planning domain that supports the execution of realistic multi-vehicle AUV/ASV missions.
- A new strategy that combines a new Goal Allocation (GA) algorithm with Temporal Planning (TP) to improve plan quality for temporal multi-vehicle tasks.
- ROSPlan integration with robot simulators to execute multi-vehicle missions.

Acknowledgement

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References

[1] J. Benton et al. Temporal planning with preferences and time-dependent continuous costs. In *ICAPS*, 2012.

[2] Michael Cashmore et al. ROSPlan: Planning in the Robot Operating System. In *ICAPS*, pages 333–341, 2015.