Reliability-Aware Multi-UAV Coverage Path Planning using a Genetic Algorithm

Extended Abstract

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ABSTRACT

Graceful degradation is a desirable trait in applications that require *coverage* with real, failure-prone robots. This paper uses methods informed by Reliability Engineering to study the Reliability-Aware Multi-Agent Coverage Path Planning (RA-MCPP) problem. An augmented stochastic framework is applied to evaluate a strategy's probability of mission completion (PoC) on 3D lattice graph environments. A Genetic Algorithm optimisation approach is then proposed to find RA-MCPP path plans which maximise PoC. It is shown that the GA provides good solutions at reasonable runtimes, complementing previous approaches which focused on global optimality guarantees at the cost of massive computation, especially for medium and large environments.

KEYWORDS

Multi-Robot Systems; Coverage Path Planning; Reliability Analysis

ACM Reference Format:
Mickey Li, Arthur Richards, and Mahesh Sooriyabandara. 2021. Reliability-Aware Multi-UAV Coverage Path Planning using a Genetic Algorithm: Extended Abstract. In *Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), Online, May 3–7, 2021*, IFAAMAS, 3 pages.

1 INTRODUCTION

Multi-agent systems offer significant advantages of reliability, resilience and fault tolerance compared to single-agent systems [7, 18]. This robustness property is especially suited to aerial robotics applications as small Unmanned Aerial Vehicles (UAVs) are prone to failure [1, 4, 6]. The Reliability-Aware Multi-Agent Coverage Path Planning (RA-MCPP) problem seeks to find coverage paths for each failure-prone UAV which will maximise the probability of mission completion within the deadline. A failure occurring in most existing mCPP methods which minimise distance [2, 8] or energy [11, 12] would require reactive re-routing through resilient methods [14, 16], likely exceeding the deadline. Preliminary work in [10] used an agent's failure model to *a-priori* find paths that maximise the probability of mission completion in 1D cyclic environments. This work extends [10] by applying reliability evaluation to 3D lattice graph environments (such as Fig 1), and proposing a genetic algorithm (GA) approach to solving RA-MCPP.

Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), U. Endriss, A. Nowé, F. Dignum, A. Lomuscio (eds.), May 3–7, 2021, Online.

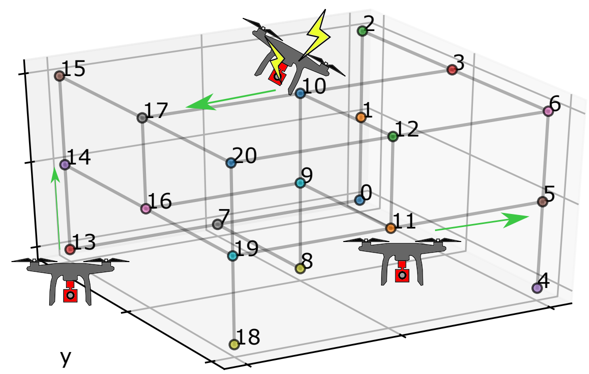

Figure 1: Consider 3 failure prone drones covering this environment. What plan might route agents such that the probability of mission completion (all points/tasks visited) is maximised?

2 MARKOV RELIABILITY EVALUATION

Let the state of the system of n agents at a time t to be $x^t = (\tau_1^t, \ldots, \tau_n^t) \in \mathbb{N}^n = \mathrm{S}$ where $\tau_i^t = \tau_i^{t-1} + 1$ each time step if the agent survives, with $\tau_i^t = \tau_i^{t-1}$ otherwise. Differing from [10], the environment is a unit graph $G(\mathbf{J}, E)$, defining a set of m discrete tasks described by the nodes $\mathbf{J} = (j_1, \ldots, j_m)$, with the edges E describing valid traversable paths between tasks. For each agent i, $f_i(t)$ and $F_i(t)$ are the failure probability and cumulative density respectively, with *Reliability* $R_i(t) = 1 - F_i(t)$ [13]. Considering the state as 'work done', instead of involving explicit locations of agents and completion of tasks, allows the decoupling of state analysis from the probability analysis with the possibility of accommodating different failure models (this paper uses a constant failure rate).
A strategy ψ then represents a set of finite connected tasks $j \in \mathbf{J}$, i.e. paths for each agent. For a strategy ψ, in each possible state x, either all tasks have been visited and the mission is completed, or not. The allocation matrix $T^\psi \in \mathbb{R}^{n \times m}$ can be defined, where the elements T_{ij}^ψ are the *first time* at which agent i is scheduled to complete the task j. Therefore a task j is considered completed by agent i if $\tau_i \geq T_{ij}^\psi$, and the **Completion Region** $\mathrm{C}_\psi \subseteq \mathrm{S}$ can be defined and computed as follows:

$$\mathrm{C}_\psi = \{x \in \mathrm{S} \mid \forall j \; \exists i \; \tau_i \geq T_{ij}^\psi\} \tag{1}$$

$$= \{x \in \mathrm{S} \mid \min_{j \in [1..m]} \max_{i \in [1..n]} \tau_i - T_{ij}^\psi \geq 0\} \tag{2}$$

Method	Small 3x3x3 (Fig. 1)		Medium 3x4x4 (Fig 2 top)		Large 4x4x4 (Fig 2 bottom)	
	PoC @ $t = 20$	comp. time (s)	PoC @ $t = 35$	comp.time (s)	PoC @ $t = 49$	comp. time (s)
ILP [10]	0.9966	(timeout) 14400	0.9514	(timeout) 14400	0.8706	(timeout) 14400
TSP + Exhaustive	0.9887	44	0.9668	4676	0.9520	11438
TSP + ILP	0.9770	13	0.9868	400	0.9706	2043
GA PoC	0.9818	100	0.8318	352	0.7808	423
GA PoC + Time	0.9881	67	0.8000	277	0.6829	537
Partition	0.8262	< 1	0.6111	< 1	0.547	< 1
Overlap Partition	0.9517	< 1	0.6764	< 1	0.3594	<1
Random Walk	0.2440	< 1	0.1194	3	0.0240	11

Table 1: Performance and computation time comparison of RA-MCPP methods on different sized environments.

The **Probability of Completion** (PoC) for strategy ψ at time t' is the sum of the probabilities of surviving to a state within the Completion Region $\mathbf{C}_\psi$:

$$PoC(\psi, t') = \sum_{x \in \mathbf{C}_\psi} p(x, t') = \sum_{x \in \mathbf{C}_\psi} \prod_{i \in [1..n]} p_i(\tau_i, t') \tag{3}$$

$$p_i(\tau, t') = \begin{cases} f_i(\tau), & \text{if } \tau < t' \\ R_i(\tau), & \text{if } \tau \geq t' \end{cases} \tag{4}$$

This evaluation runs in $O(nm)$. This method focuses on static, pre-allocated strategies. Refer to [10] for a discussion on non-static and reactive strategies.

3 PATH BASED GENETIC ALGORITHM

Multi-agent coverage can be considered equivalent to the Multiple Travelling Salesman Problem (mTSP) [15]. A Genetic Algorithm (GA) approach was chosen as it has been successfully applied to solving mTSP [3, 9, 17]. The chromosome represents a RA-MCPP strategy allocation T^ψ. In particular, each agent's path is encoded as its first visit to each task. The *population* is of size μ, initialised by environment partitioning. Two chromosome *fitness* functions are defined: (i) only PoC, and (ii) A weighted sum of PoC and the time taken to completion with no failures ('POC+time') in order to encourage valid paths in larger environments. The optimisation goal is thus to maximise the fitness function. Furthermore as shortest paths between tasks are evaluated as part of the fitness function, backtracking routes can also be found for environments with no Hamiltonian Cycles where the previous Linear Program [10] method would be infeasible. The following operators are implemented for reproduction. *Mutations*: (1) *swap-mutation* randomly swaps consecutive tasks from a random agent. (2) *add-mutation* and (3) *delete-mutation* are used to add or remove tasks from a random agent in the chromosome. (4) *roll-mutation* randomly cycles the starting task of a random agent by a random amount in the chromosome. *Crossover* (both based on [9]): (1) *sequence-crossover* chooses a random agent from each chromosome. A split point on each agent's path is also randomly chosen, and the paths are spliced together. (2) *path-crossover* chooses a random agent from each chromosome and swaps their respective paths. Finally, for *selection* operators, *random selection* is used for reproduction, and *tournament selection* is used for constructing the next generation.

The evaluation was implemented using DEAP [5] with 2000 generations and a population of 100, crossover and mutation probabilities set to 0.5 and 0.3 respectively, constant failure rate $\lambda = 0.01$ and run on 8-core 1.8Ghz CPU. Table 1 shows a comparison of performance and computational time with existing methods on cubic-lattice environments (Figures 1 and 2). The partition methods represent existing mCPP methods and whilst quick, are much less reliable. The ILP [10] and 'TSP phasing' methods (agents allocated by exhaustive evaluation or an ILP on a cycle found by solving the Travelling Salesman Problem) often found highly reliably paths, but computational times clearly scale poorly as environment size increases. Conversely, both highlighted GA methods provide relatively good solutions, but are an order of magnitude faster for large environments, potentially trading off highly reliable strategies for computation time.

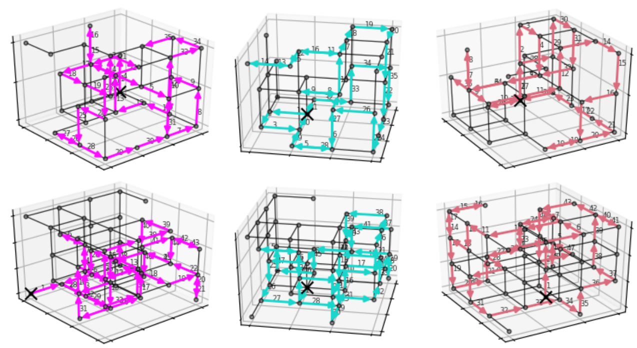

Figure 2: Medium (Top) and Large (Bottom) graph environments running GA PoC Agent Paths

4 CONCLUSIONS

In this paper, the novel Reliability-Aware Multi-Agent Coverage Path Planning (RA-MCPP) problem is investigated. An updated reliability evaluation method for the probability of completion metric in graph-based environments is presented. Finally, a Genetic Algorithm approach to solving RA-MCPP is compared to existing approaches and shown to sit within the trade-space providing reasonable solutions for reasonable computation times. Future work will focus on applying RA-MCPP to real Inspection scenarios. This will include investigate the effect of relaxing the current set of assumptions, namely solving the problem in continuous space and time.

ACKNOWLEDGMENTS

This work has been funded by the UK Engineering and Physical Sciences Research Council (EPSRC) iCASE with Toshiba Research Europe Ltd.

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