On-line Estimators for Ad-hoc Task Allocation

Extended Abstract

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ABSTRACT

It is essential for agents to work together with others to accomplish common missions without previous knowledge of the team-mates, a challenge known as ad-hoc teamwork. In these systems, an agent estimates the algorithm and parameters of others in an on-line manner, in order to decide its own actions for effective teamwork. Meanwhile, agents often must coordinate in a decentralised fashion to complete tasks that are displaced in an environment (e.g., in foraging, demining, rescue or fire control), where each member autonomously chooses which task to perform. By harnessing this knowledge, better estimation techniques would lead to better performance. Hence, we present *On-line Estimators for Ad-hoc Task Allocation*, a novel algorithm for team-mates' type and parameter estimation in decentralised task allocation. We ran experiments in the level-based foraging domain, where we obtain lower error in parameter and type estimation than previous approaches, and a significantly better performance in finishing all tasks.

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1 INTRODUCTION

In ad-hoc teamwork, agents collaborate to accomplish common tasks without pre-knowledge of each other, nor prior coordination or communication protocols. Hence, it is a beneficial model for solving issues in real-world domains, like rescue robots from different organisations which are urgently brought together to aid in a natural disaster – e.g., earthquakes. In these scenarios, designing coordination/communication protocols would take time, and resources. Avoiding such delays and funding usage could save lives.

Instead of learning models from scratch, it is common in the literature to assume a set of possible types [4, 5], reducing the problem to estimating the type of each agent. This approach is more applicable, as it does not require such a large number of observations, and can be more easily applied in an on-line manner. Types could be built based on previous experiences [6] or may be derived from the domain [1]. Additionally, having parameters for each type allowed more fine-grained models [2]. However, previous works were not specifically designed for decentralised task allocation, missing an opportunity to obtain better performances in this relevant scenario for multi-agent collaboration.

Note that individual agents do not need to share the same representation of the problem as decentralised task allocation, and run algorithms that explicitly "choose" tasks. They could be developed by different parties, and could use different paradigms. All we need are problems that can be modelled as decentralised task allocation for *our* ad-hoc agent. Similarly, a global allocation algorithm is unfeasible in our scenario: agents developed by others would not necessarily follow commands from a central entity, and we are not assuming any communication protocol.

Therefore, for better estimation of team-mates types and parameters in decentralised task allocation, we introduce our *novel algorithm* called *On-line Estimators for Ad-hoc Task Allocation* (OEATA). We run experiments in a collaborative foraging domain, where agents collect "heavy" boxes together. We obtain a lower error in parameter and type estimations in comparison with the state-of-the-art, leading to significantly better performance in task execution.

2 METHODOLOGY

We consider one agent ϕ, in the same environment as a set of agents Ω ($\phi \notin \Omega$). ϕ must maximise team performance, but it does not know how agents $\omega \in \Omega$ may behave at each state. As in previous works [2], we consider that agents in Ω can be defined by a type $\theta \in \Theta$, and by a vector of parameters $\mathbf{p}$, each in a fixed range. Estimating θ and $\mathbf{p}$ allows ϕ to estimate ω's behaviour, leading to better decision-making. Hence, we introduce OEATA for better parameter and type estimations in ad-hoc decentralised task allocation.

In OEATA, we have a set of *estimators* for each agent ω and each type θ ($\mathbf{E}^{\theta}_{\omega}$), which have a fixed size N. An *estimator e* is a tuple, $(\mathbf{p}_e, s_e, \tau_e, c_e, f_e)$: $\mathbf{p}_e$ is a parameter vector; s_e is the last *choose target state* (*choose target state* is the state s_τ when ω tries to choose a new task τ' after completing the task τ); τ_e is the task that ω would try to complete when having parameter $\mathbf{p}_e$ and type θ; c_e holds the number of times that e was successful in predicting ω's next task; f_e holds the number of *consecutive* failures. The s_e states are updated when another agent collects the predicted task τ_e. The *choose target state* of the agent is then estimated as the one stored in the *estimator e* with highest c_e across all sets $\mathbf{E}^{\theta}_{\omega}$. These will be used to compose the agent's history, when updating c_e.

All *estimators e* are initialised in the first step, and $\mathbf{p}_e$ of each e can be initialised with random values (e.g., from the uniform distribution). For all *estimators e*, s_e is set as the initial state of

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