Approximating cost structures in decentralized auctions and optimization for multi-agent task allocation

PhD Proposal

ONERA, Toulouse, France

February 2024

Keywords

Multi-agent systems, auctions, coordination, approximate bidding, reinforcement learning

Context and Motivations

In the context of multi-robot or multi-vehicle applications, such as search-and-rescue, urban UAV traffic management, or multi-agent pick-up and delivery, coordination is a key element that provides a multi-perspective and multi-skill approach to problems hardly covered by single robots. Yet, from the performance viewpoint, optimizing resource usage, mission duration and quality, coordination is a hard problem. In fact, when (semi-)autonomous agents have to decide which tasks to fulfill, which path to follow or which multi-agent action to perform, one has to solve hard combinatorial problems such as task allocation [12], resource allocation [2], multi-agent pathfinding [14] or multi-agent trajectory repair [9]. Such problems can be solved using a classical centralized approach, such as combinatorial auctions or mathematical programming [13].

However, in the context of missions where the decisions might be decentralized to (i) improve robustness to disconnections or (ii) improve reactiveness (without waiting for a central authority to make the decision), decentralizing such decision-making is crucial. Moreover, these algorithms strongly rely on the capability for agents to bid over items (tasks/actions/resources/etc.) or bundle of items. In classical auctions or mathematical programming approaches, this bidding requires to be able to valuate each combination (or some of them) of items, or to use more compact representations of sets of interdependent items [4]. This information may take the form of large tables or graphs, may be too large to be computed at fast pace or to be exchanged within unreliable communication infrastructure. Moreover, in the case of multi-agent tasks (requiring several agents to be performed), as in CBGA algorithm [1], or in the case of multi-mode tasks (tasks that can be fulfilled in different manners) as in MM-CBGA algorithm [10], data structures are becoming even larger (to process and to communicate).

Besides auctions, such table-based decision representation is also at the core of some distributed optimization algorithms (DCOP) [6], especially inference-based ones, such as DPOP or Max-Sum, and we aim at providing generic theoretical tools to use both in auctions and DCOPs domains.

In the domain of reinforcement learning, such an approximation and compacting problem has been handled using deep neural networks or other approximation functions to represent and functionally approximate Q-tables for instance [7]. In the domain of multi-agent pick and delivery, attention models have been used to form collectives and allocate tasks [5]. We aim at exploring the use of such techniques in the context of auctions and DCOPs.

Objectives

The idea of this thesis is thus to bring approximation to bidding to implement decentralized auctions and distributed inference with good reactiveness and low communication load. The idea is to first devise approximation schemes for mono-agent mono-mode tasks decentralized allocation, in the consensus-based bundle allocation framework (CBBA) [3], and then to extend the models for multi-agent tasks (CBGA) and multi-mode tasks (MM-CBGA). In a second time, we will investigate how to implement these approximation schemes to the inference-based DCOP framework, in complete (DPOP) and incomplete (Max-Sum) solution methods.

We previously applied auctions and DCOP domains such as Earth observation [9, 10], Unmanned Aircraft System Traffic Management (UTM) [8], and multi-robot missions [11]. We thus envision to implement and evaluate the theoretical and algorithmic contributions of this thesis to one or more of these application domains.

Hosting institution

The *Office national d'études et de recherches aérospatiales* (ONERA) is the French national aerospace research lab. The PhD student will be hosted at ONERA, Toulouse, France (`https://www.onera.fr/en/centers/toulouse`), and will have opportunities to visit IIIA-CSIC, in Barcelona.

Collaboration

The PhD thesis will be jointly supervised by ONERA (Toulouse, France) and IIIA-CSIC (Barcelona, Spain).

Supervisors

- Pr. Gauthier Picard, Directeur de recherche, ONERA
- Dr. Filippo Bistaffa, Tenured Researcher, IIIA-CSIC
- Pr. Juan A. Rodríguez-Aguilar, Research Professor, IIIA-CSIC

Profile and skills required

Master-level with strong skills in AI, optimization, multi-agent, RL

How to apply

Applications (CV, motivation letter, referees, and grades) should be sent to `gauthier.picard@onera.fr, juanantonio.rodriguez@csic.es, filippo.bistaffa@iiia.csic.es` with the subject `"Application to PhD position TIS-DTIS-2024-14"`.

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Important dates

- Application deadline: April 1st, 2024
- Interviews: April 15-22, 2024
- Final decision: April 30, 2024
- Start of PhD study: October 2024 (can be adjusted)

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