



Multi-agent team cooperation: A game theory approach[☆]

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ABSTRACT

The main goal of this work is to design a team of agents that can accomplish consensus over a common value for the agents' output using cooperative game theory approach. A semi-decentralized optimal control strategy that was recently introduced by the authors is utilized that is based on minimization of individual cost using local information. Cooperative game theory is then used to ensure team cooperation by considering a combination of individual cost as a team cost function. Minimization of this cost function results in a set of Pareto-efficient solutions. Among the Pareto-efficient solutions the Nash-bargaining solution is chosen. The Nash-bargaining solution is obtained by maximizing the product of the difference between the costs achieved through the optimal control strategy and the one obtained through the Pareto-efficient solution. The latter solution results in a lower cost for each agent at the expense of requiring full information set. To avoid this drawback some constraints are added to the structure of the controller that is suggested for the entire team using the linear matrix inequality (LMI) formulation of the minimization problem. Consequently, although the controller is designed to minimize a unique team cost function, it only uses the available information set for each agent. A comparison between the average cost that is obtained by using the above two methods is conducted to illustrate the performance capabilities of our proposed solutions.

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1. Introduction

Sensor networks (SN), and in general, unmanned system networks (UMSN) are currently one of the strategic areas of research in different disciplines, such as communications, controls, and mechanics. These networks can potentially consist of a large number of agents, such as unmanned aerial vehicles (UAV), unmanned ground vehicles (UGV), unmanned underwater vehicles (UUV), and satellites. Wireless UMSN provide significant capabilities and numerous applications in various fields of research are being considered and developed. Some of these applications are in home and building automation, intelligent transportation systems, health monitoring and assisting, space explorations, and commercial applications (Sinopoli, Sharp, Schenato, Schafferthim, & Sastry, 2003). There are also military applications in intelligence, surveillance, and reconnaissance (ISR) missions in the presence of environmental disturbances, vehicle failures, and in battlefields

subject to unanticipated uncertainties and adversarial actions (Bošković, Li, & Mehra, 2002).

One of the prerequisites for these networked agents that are intended to be deployed in challenging missions is team cooperation and coordination for accomplishing predefined goals and requirements. Cooperation in a network of unmanned systems, known as formation, network agreement, flocking, consensus, or swarming in different contexts, has received extensive attention in the past several years. Several approaches to this problem have been investigated within different frameworks and by considering different architectures (Arcak, 2006; Gazi, 2002; Lee & Spong, 2006; Olfati-Saber & Murray, 2002, 2003b,c, 2004; Paley, Leonard, & Sepulchre, 2004; Ren, 2007; Ren & Beard, 2004; Semsar & Khorasani, 2006; Stipanović, Inalhan, Teo, & Tomlin, 2004; Xiao & Wang, 2007).

An optimal approach to team cooperation problem is considered in Raffard, Tomlin, and Boyd (2004) and Inalhan, Stipanović, and Tomlin (2002) for formation keeping and in Bauso, Giarre, and Pesenti (2006) and Semsar-Kazerooni and Khorasani (2007a,b,c, 2008, 2009) for consensus seeking. The approach in Inalhan et al. (2002) is based on individual agent cost optimization for achieving team goals under the assumption that the states of the other team members are constant. The concept of Nash equilibrium is used for design of optimal controllers. In order to solve an optimal consensus problem, the authors in Bauso et al. (2006) have assumed an individual agent cost for each team member. In evaluating the minimum value of each individual cost, the states of the other agents

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are assumed to be constant. The work in Semsar-Kazerooni and Khorasani (2007a,b,c, 2008, 2009) have avoided and removed the above restricting assumptions by decomposing the control input of each team member into local and global components. The global component (referred to as the interaction term) is designed such that individual agent cost function is minimized in a distributed manner. In all the above referenced work the optimal problem is based on the individual cost definition for team members. However, to the best of the authors' knowledge, a single team cost function formulation has been proposed in only a few works (Fax, 2002; Raffard et al., 2004; Semsar & Khorasani, 2007). In Fax (2002), optimal control strategy is applied for formation keeping and a single team cost function is utilized. The authors in Raffard et al. (2004) assumed a distributed optimization technique for formation control in a leader–follower structure. The design is based on dual decomposition of the local and global constraints. However, in that approach, the velocity and position commands are assumed to be available to the entire team. In Semsar and Khorasani (2007), a centralized solution is obtained by using a game theoretic approach.

It is worth noting that a very few work in this domain use a design-based approach. In fact, many of the earlier work in the literature have focused on analysis only (Jadbabaie, Lin, & Morse, 2003; Olfati-Saber, 2006; Olfati-Saber & Murray, 2004; Ren & Beard, 2005; Tanner, Jadbabaie, & Pappas, 2007). However, the main contribution of this paper is to introduce a novel design-based approach to formally design a controller (the consensus algorithm) to address the output consensus over a common value using a single team cost function within a game theoretic framework. The advantage of minimizing a cost function that describes the total performance of the team is that it can provide a better insight into performance of the entire team when compared to individual agent performance indices. However, the potential main disadvantage of this formulation is clearly the requirement of availability of full information set for control design purpose. In the present work this problem is alleviated and the imposed information structure of the team is taken into account by using a linear matrix inequality (LMI) formulation. For this purpose, a decentralized optimal control strategy that was initially introduced in Semsar-Kazerooni and Khorasani (2007b, 2008) is used to design controllers based on minimization of individual costs. Since in this approach the solution is obtained through minimization of local cost functions we have at most a person-by-person optimality. However, if a cost function describing the total performance is minimized a lower team cost as well as lower individual costs may be achieved. Subsequently, the idea of cooperative game theory is used to minimize a team cost function which is a linear combination of the cost functions that are used in the optimal approach. This will guarantee that individual cost functions have the minimum possible values for the given team mission. To obtain a solution that is subject to a given information structure as well as to guarantee consensus achievement, a set of LMIs is used to constrain the controller to be designed for the entire team.

The organization of the paper is as follows: In Section 2, background information is presented. In Section 3, cooperative game theory is introduced. Application of the game theory to the multi-agent team problem, the design of a semi-decentralized optimal control, and solutions to the corresponding min–max problem are presented in Section 4. Finally, simulation results are conducted and conclusions are stated in Sections 5 and 6, respectively.

2. Background information

Multi-agent teams: Assume a set of agents $\Omega = \{i = 1, \dots, N\}$, where N is the number of agents. Each member of the team which is denoted by i is placed at a vertex of the network information

graph. The dynamical representation of each agent is governed by

$$\dot{X}^i = A^i X^i + B^i u^i, \quad X^i \in \mathbb{R}^n, u^i \in \mathbb{R}^m, i = 1, \dots, N \quad (1)$$

$$Y^i = C^i X^i, \quad Y^i \in \mathbb{R}^q \quad (2)$$

where X^i denotes the state vector, u^i denotes the input vector, and Y^i denotes the output vector of agent i and A^i , B^i and C^i are matrices of appropriate dimensions.

Information structure and neighboring sets: In order to ensure cooperation and coordination among team members, each member has to know the status of the other members, and therefore members have to communicate with each other. For a given agent i , the set of agents connected to it via communication links is called a neighboring set N^i . The existence of a link between two agents in general may refer to the availability of information of one agent to the other one, in other words $\forall i = 1, \dots, N, N^i = \{j = 1, \dots, N | (i, j) \in E\}$, where E is the edge set that corresponds to the underlying graph of the network. It is assumed that the graph describing the information structure is connected.

Laplacian matrix (Fax & Murray, 2004): This matrix is used to describe the graph associated with information exchanges in a network of agents, i.e. G , and is defined as $L = [L(i, j)]_{N \times N}$

$$L(i, j) = \begin{cases} d(i) & i = j \\ -1 & (i, j) \in E \text{ and } i \neq j \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where $d(i)$ is equal to the cardinality of the set N^i (Olfati-Saber & Murray, 2003a), $|N^i|$, and is called the degree of vertex i . For an undirected graph, the degree of a vertex is the number of edges incident to that vertex (total number of links connected to that vertex). For directed graphs, instead of the degree either the in-degree or the out-degree might be used (the total number of the links entering or leaving a node). This matrix has vector $\mathbf{1}$ as its right eigenvector corresponding to its zero eigenvalue.

Leaderless (LL) structure: In this structure no external command is provided to the members of the team, and the goal is to make the agents' output, e.g. velocity, converge to a common value which is decided upon by the team members.

Model of interaction between the team members: Assume that the dynamical model of each agent is given by Eqs. (1) and (2). This model defines an isolated agent of the team, but in reality agents have some interactions through the information flow that exists among the neighboring agents. In Semsar-Kazerooni and Khorasani (2007b, 2008), it was shown that each member's dynamics can be described by the following model that incorporates the interaction terms, namely

$$\begin{cases} \dot{X}^i = A^i X^i + B^i u^i \\ u^i = u_l^i + u_g^i, \quad u_g^i = \sum_{j \in N^i} F^{ij} Y^j \\ Y^i = C^i X^i \end{cases} \quad (4)$$

where u_l^i, u_g^i are the decomposition of the input signal into the "local" and the "global" control terms. As discussed in Semsar-Kazerooni and Khorasani (2007c, 2008), the local term for each agent is designed using the agents own output vector whereas the global control utilizes the information received from other agents in its neighboring set. The "global" control term $u_g^i(Y^j) = \sum_{j \in N^i} F^{ij} Y^j$ is also denoted as the interaction term, where F^{ij} is the interaction matrix to ensure compatibility in the agent's input and output channels dimensions. The proposed interaction terms are used in order to overcome the relative specifications and dependencies of individual agent goals on other agents' outputs or states as described in Semsar-Kazerooni and Khorasani (2007c,

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