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Decision Support

Approximate representation of the Pareto frontier in multiparty negotiations: Decentralized methods and privacy preservation☆

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ABSTRACT

Multiparty negotiations have drawn much research attention in recent years and an important problem is how to find a Pareto optimal solution or the entire Pareto frontier in a decentralized way. Privacy preservation is also important in negotiation analysis. The main aim of this paper is to find an approximate representation of the Pareto frontier in a decentralized manner and meanwhile, all parties' privacy can be effectively protected. In this paper, we propose a decentralized discrete-time algorithm based on a weight sum method and the well-known subgradient optimization algorithm, where a mediator works as a coordinator to help negotiators. The proposed algorithm is easily executable, and it only requires the mediator to compute a weighted average of the noisy estimates received from negotiators and negotiators to follow a subgradient optimization iteration at this weighted average. The proposed algorithm can generate an approximate Pareto optimal solution for one particular weight vector and an approximate representation of the Pareto frontier by varying appropriately weight vectors. The approximation error between the obtained approximate representation and the Pareto frontier can be controlled by the number of iterations and the step-size. Moreover, it also reveals that the proposed algorithm is privacy preserving as a result of the random disturbance technique and the weighted average scheme used in this algorithm.

1. Introduction

Negotiation analysis has drawn much research attention in last decades due to its wide applications in electronic commerce, artificial intelligence, economics and operations research. The development of powerful methods and decision tools for seeking Pareto optimal solutions (POSs) in negotiation analysis is interesting since the negotiators frequently fail to achieve efficient agreements in practice (Raiffa, 1982; Sebenius, 1992). This may be caused by the numerous issues to be negotiated over and the limited knowledge about the other negotiators' interests.

Many decentralized methods for computing POSs have been proposed in the literature (Ehtamo et al., 1999a; Ehtamo, Kettunen, & Hamalainen, 2001; Ehtamo, Verkama, & Hamalainen, 1999b; Heiskanen, 1999, 2001; Heiskanen, Ehtamo, & Hamalainen, 2001; Kitti & Ehtamo, 2007; Sehgal & Pal, 2005). A method is called decentralized if its use does not require the parties to know each others' value functions nor does any one outsider take the full knowledge of all the value functions. In decentralized Pareto-optimality seeking methods, typically an interactive procedure is designed between the negotiators and a mediator, who works as a neutral coordinator helping the negotiators to seek POSs.

Most of decentralized methods can be classified into two classes: constraint proposal methods (Ehtamo et al., 1999a; Ehtamo, Verkama, & Hamalainen, 1996; Heiskanen, 2001; Heiskanen et al., 2001; Kitti & Ehtamo, 2007; Teich, Wallenius, Wallenius, & Zionts, 1995; Verkama, Ehtamo, & Hamalainen, 1996) and improving direction methods (Ehtamo et al., 2001; Ehtamo et al., 1999b; Teich, Wallenius, Wallenius, & Zionts, 1996). The constraint proposal methods are based on the fact that under some mild convexity (concavity) assumptions on the objective functions, there exists a joint tangent hyperplane for negotiators' indifference curves at a POS. In the execution process, the mediator adjusts

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a hyperplane going through a given reference point following a numerical iteration scheme until the negotiators' most preferred points on the hyperplane (the optimal solutions of some optimization problem) coincide. The final coincident point is a POS. By varying the reference point, the constraint proposal methods can generate an approximation for the Pareto frontier. Teich et al. (1995), Ehtamo et al. (1999a, 1996) and Kitti and Ehtamo (2007) consider the two-party case, while Verkama et al. (1996), Heiskanen et al. (2001) and Heiskanen (2001) discuss the more general multiparty case. In joint improvement methods, a joint improving direction is searched from a tentative agreement and a POS will be obtained if a joint improving direction can no longer be found. The authors in Ehtamo et al. (1999b) showed that the improving direction method will converge in a two-party case provided proper conditions hold, while the method was generalized to multiple-party multiple-issue case in Ehtamo et al. (2001). The authors in Teich et al. (1996) proposed serval heuristic methods for seeking joint improvements and some extensions of the proposed methods for approximating the Pareto frontier in a two-party resource allocation negotiations.

The authors in Heiskanen (1999) proposed a decentralized method based on weight sum and decomposition technique to generate all the POSs of the Pareto frontier in multiparty negotiations, where the scalarized objective is decomposed by introducing a decision variable for each party and then applying the dual decomposition technique. The decomposition results in a separable problem which is solved iteratively with each party solving its individual optimization problem, whereas the mediator updates the parameters of the optimization problems according to the optimal solutions received from the parties. When the parties' optimal solutions converge, the common optimal solution is guaranteed to be Pareto optimal. Moreover, decentralized methods have also been proposed to solve other interesting problems, for instance, cooperative optimization (Fulga, 2007; Nedić & Ozdaglar, 2009; Nedić, Ozdaglar, & Parrilo, 2010), online learning (Yan, Sundaram, Vishwanathan, & Qi, 2013) and eigenvector computation (Pathak & Raj, 2011).

Privacy preservation is an extremely important issue in negotiations. Negotiators desire to achieve an efficient agreement, but they are usually unwilling to disclose their private information to other negotiators because of some strategic reasons (Raiffa, 1982). However, most of the existing decentralized methods did not fully consider the privacy preservation problem. For instance, in constraint proposal methods and improving direction methods, the negotiators are required to report the optimal solutions of their own optimization problems to the mediator, or to answer the question which one of two available agreements they prefer to. These methods will lead to privacy disclosure inevitably in the sense that the mediator can infer some information about negotiators' objective functions based on the received information from negotiators.

In this paper, we consider the Pareto frontier approximate representation problem in multiparty negotiations. In our problem setup, we assume the negotiators can only exchange information with the mediator directly from the viewpoint of privacy preservation, and all parties including the mediator are semi-honest, that is, all parties follow the algorithm correctly but keep the record of all their computations. In this paper, we are interested in the following two problems: the first one is how to design an easily executable decentralized method to find an approximate representation of the Pareto frontier, and the second one is whether negotiators' privacy can be effectively protected during the algorithm execution.

Our proposed algorithm is discrete-time and based on a weight sum method and the well-known subgradient optimization algorithm. In each round of algorithm iteration, the negotiators first report their noisy estimates to the mediator and then the mediator takes a weighted average of all the estimates. Finally, the mediator reports this weighted value to negotiators and the negotiators update their estimates at the next step from the weighted average value along a negative subgradient direction. The proposed algorithm can generate an approximate POS for one particular weight vector with a geometric convergence rate and a discrete approximate representation of the Pareto frontier by systematically varying the weight vectors. The approximate error between the obtained approximation representation and the Pareto frontier can be characterized in terms of the system parameters such as the number of iterations and the (constant) step-size.

The proposed method is decentralized since it does not require any party to take the full knowledge of the multiparty negotiation problem. In fact, it only requires that each negotiator makes its own optimization iteration and the mediator computes the weighted average of the negotiators' estimates. Moreover, it is also privacy preserving observing that it can prevent the mediator from learning anything about negotiators' estimates due to the random disturbances in the transmitted estimates from negotiators to the mediator, and also prevent each negotiator from learning anything from other negotiators even though the received weighted average contains the information of other negotiators' estimates since all the negotiators do not know the weight taken by the mediator in the weighted average computation.

Compared with the constraint proposal methods and improving direction methods, our algorithm is easily executable and can save a lot of computations. In our algorithm, the negotiators are not required to report the optimal solutions of their own optimization problems and their most preferred points on constraint sets to the mediator, and only their estimates for POSs are required to be reported to the mediator. Compared with the methods in Yan et al. (2013), Nedić and Ozdaglar (2009), Nedić et al. (2010), Lou, Hong, Xie, Shi, and Johansson (2016) and Lou, Shi, Johansson, and Hong (2014), negotiators are not allowed to communicate with each other from the viewpoint of privacy preservation. Moreover, different from most of the existing algorithms, we fully consider the privacy preservation problem to avoid privacy disclosure because of the conflict of negotiators' interest.

The rest of this paper is organized as follows. The preliminaries on multiparty negotiation and problem formulation are presented in Section 2. A fully trusted decentralized POS generating algorithm and a modified privacy-preserving version are introduced in Section 3. Section 4 presents the proposed decentralized discrete approximate representation generating algorithm and the approximate error result. The numerical examples are given in Section 5. Some concluding remarks are given in Section 6.

2. Preliminaries and problem formulation

2.1. Preliminaries on multiparty negotiations

A multiparty negotiation problem (MNP) is usually described as

$$\begin{aligned} &\text{minimize} \;\; f(x) = \big(f_1(x), \dots, f_n(x)\big) \\ &\text{subject to} \;\; x \in X_i, \;\; i = 1, \dots, n. \end{aligned} \tag{1}$$

Here $n \geq 2$ is the number of negotiating parties; $X_i \subseteq \mathbb{R}^m$ and $f_i : \mathbb{R}^m \to \mathbb{R}$ are the closed convex constraint set and the convex value function of negotiator i, respectively, $i = 1, \dots, n$; m is the number of negotiated issues. We assume throughout this paper that the constraint sets $X_i, i = 1, \dots, n$ are bounded and have a nonempty intersection. The nonempty feasible set of MNP (1) is denoted as $X = \cap_{i=1}^{n} X_i$.

Let $\mathcal{X}_E$ denote the set of all Pareto optimal solutions (POSs) of MNP (1), i.e., $x^* \in \mathcal{X}_E$ if and only if $x^* \in X$, and there is no $x \in X$ such that $f_i(x) \leq f_i(x^*)$ for all i, and with strict inequality for at