Hoz, E. de la, Lopez-Carmona, M.A., Klein, M., Marsa-Maestre, I., 2012, "Hierarchical Clustering and Linguistic Mediation Rules for Multiagent Negotiation" (Extended abstract), Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2012), Conitzer, Winikoff, Padgham, and Van der Hoek (eds.), Vol. 3, p.1259-1260.

Available at http://dl.acm.org/citation.cfm?id=2343896.2343952

Hierarchical Clustering and Linguistic Mediation Rules for Multiagent Negotiation

(Extended Abstract)

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ABSTRACT

We propose a framework based on Hierarchical Clustering (HC) to perform multiagent negotiations where we can specify the type of agreements needed in terms of utility sharing among the agents.The proposed multi-round mediation process is based on the analysis of the agents' offers at each negotiation round and the generation of a social contract at each round as a feedback to the agents, which explore the negotiation space to generate new offers. This mechanism efficiently manages negotiations following predefined consensus policies avoiding zones of no agreement.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*heuristic methods*; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*multiagent systems*; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*coherence and coordination*

General Terms

Algorithms, Design, Experimentation

Keywords

Teamwork, coalition formation, coordination, negotiation

1. INTRODUCTION

The type of consensus employed to reach and agreement should be taken into consideration as an integral part when building multiparty negotiation protocols. In this paper, we propose HCPMF, a Hierarchical Consensus Policy based Mediation Framework for Multi-Agent Negotiation. Globally, HCMPF allows to efficiently search for agreements following predefined consensus policies.The protocol is designed to minimize the revelation of private information.

Appears in: *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2012)*, Conitzer, Winikoff, Padgham, and van der Hoek (eds.), 4-8 June 2012, Valencia, Spain.

2. THE NEGOTIATION PROTOCOL

Each agent sends the mediator an ***initial contract offer***. Based on the received offers, the mediator applies the ***HC algorithm*** [2] to form *clusters of agents*. The cluster with the highest number of agents is selected. Then, the mediator applies the ***OWA operator*** to the offers in the selected cluster to obtain a *feedback contract*. The OWA operator synthesizes the consensus policy to apply. Finally, the mediator verifies if the deadline has been reached. If so, negotiation ends with an agreement on the feedback contract. Otherwise, the mediator computes the ***group distance***, which is a distance estimate to the current feedback contract from the offers in the cluster. If the group distance is below a threshold the negotiation ends with an agreement on the feedback contract. If it is not, the mediator proposes the ***feedback contract*** to the agents. Each agent performs a *local exploration* of the negotiation space using a variation of ***GPS*** [1] to generate a *new offer*. The agent's exploration considers the feedback contract and its utility. The new offer is sent to the mediator, which iterates the process.

3. THE MEDIATION MECHANISMS

The goal of the mediation process is to provide useful feedback to the agents to guide the joint exploration of the negotiation space. This feedback is represented by the *feedback contract*. For the contracts in the highest sized cluster O_{kc}, the centroid $\vec{c_k}$, we compute the distances D_{kc} from the contracts to the centroid and the set of direction vectors R_{kc} from the centroid to the contracts. The OWA operator will be applied to these values in order to obtain the feedback contract. To assess the convergence to a solution the mediator also computes the *group distance* as the OWA-weighted distances to the feedback contract. While the purpose of HC is to avoid zones of no agreement, the aim of using OWA operators is to apply a predefined consensus policy.

Our goal is to elicit a function M, the *mediation rule*, which takes $\vec{c}_k$, D_{kc} and R_{kc} in order to obtain a feedback contract following a consensus policy. M describes the process of combining the individual agents' preferences. Our final objective is to define consensus policies in the form of a linguistic agenda. For example, the mediator could make decisions following mediation rules like *"Most* agents must be satisfied by the contract".

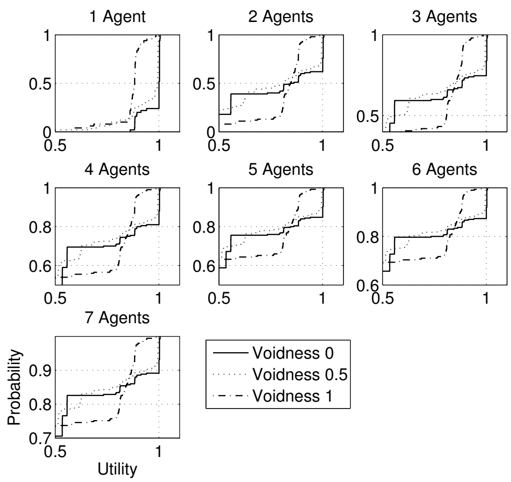

Figure 1: Cumulative distributions of utilities for the *complex negotiation scenario.*

The above statements are examples of *quantifier guided aggregations*. Any relative linguistic quantifier can be expressed as a fuzzy subset Q of the unit interval $I = [0, 1]$ [3]. It has been shown [3] that the OWA weights can be parametrized using this kind of functions. Under the quantifier guided mediation approach a group mediation protocol is expressed in terms of a linguistic quantifier Q indicating the proportion of agents whose agreement if necessary for a solution to be acceptable. First, we will express the mediation rule using the proper Q and then we will derive the OWA weights from Q. One feature which distinguishes the different types of mediation rules is the power of an individual agent to eliminate an alternative. In order to capture this idea, we use the *Value Of Individual Disapproval* (VOID) [3], which is defined as $VOID(Q) = 1 - \int_0^1 Q(y)dy$.

Finally, the feedback contract at round k is generated in the direction pointed by $\vec{v}$ from the origin $\vec{c}_k$, where vector $\vec{v}$ results from applying the vectorial OWA operator to the direction vectors. The distance at which the feedback contract is generated is obtained by applying the scalar OWA operator to the distances to the centroid. The group distance is a measure of closeness to an agreement. We take the distance to the offers in the cluster from the feedback contract to estimate the group distance. Again, we use W to OWA-weight the distance estimate and consider the consensus policy. If the group distance falls below a threshold, the negotiation ends with an agreement on the feedback contract.

4. EXPERIMENTAL EVALUATION

In the first experimental setup we have considered 7 agents. Utility functions are built using an aggregation of two randomly located *Bell functions.*The radius and height of each bell are randomly distributed within the ranges $r_i \in [20, 35]$ and $h_i = [0.1, 1]$. The probability for an agent to concede (i.e. to attend exclusively the feedback contract) is modelled for each agent using a probability value obtained from a uniform distribution between 0.25 and 0.5. We tested the performance of the protocol for 3 different consensus policies using the quantifier $Q_p(y) = y^p$.

Each experiment consist of 100 negotiations where we capture the utilities achieved by each agent. To analyze the results we first build a 7 agents$\times$100 negotiations utility matrix where each row provides each agent's utilities and each column is a negotiation. The matrix is then reorganized such that each column is individually sorted from higher to lower utility values. Given the matrix, we form 7 different utility groups: a first group named *group level 1* where we take the highest utility from each negotiation (i.e. the first row), a second group named *group level 2* with the two first rows and so on. We have used the Kaplan-Meier estimate of the cumulative distribution function (*cdf*) of agents' utilities for each group. The *cdf* estimates the probability of finding agent's utilities below a certain value. The rationale behind using grouping in the analysis is to evaluate the ability of the protocol to find solutions which satisfy groups of agents.

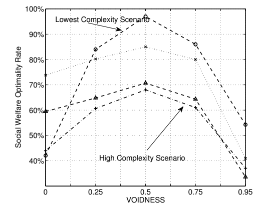

Figure 2: Social Welfare Optimality Rate vs VOID.

The results also show that as VOID increases, the mediator biases the search for agreements where more agents are satisfied at the expense of the individual satisfaction level. In general, it is worth noting that the application of a consensus policy may incur in a cost in terms of social welfare. In a second experimental setup we have considered 7 agents, 2 issues and 4 different types of negotiation spaces in increasing complexity to evaluate this issue. Figure 2 shows the social welfare measurements (sum of utilities) for different VOID degrees.

5. CONCLUSION

The negotiation framework presented opens the door to a new set of negotiation algorithms where consensus criteria may play an important role. HCPMF allows to perform multiparty negotiations where mediator guides the joint exploration of a solution by using aggregation rules which take the form of linguistic expressions. These rules are applied over the agents' offered contracts in order to generate a feedback contract which is submitted to the agents in order to guide their exploration, using HC To avoid zones of no agreement the mediator. We showed empirically that HCPMF efficiently manages negotiations following predefined consensus policies, which has been modelled using OWA operators.

6. REFERENCES

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