Contracting Strategy based on Markov Process Modeling

Sunju Park and Edmund H. Durfee

Artificial Intelligence Laboratory
The University of Michigan
Ann Arbor, MI 48109-2110
{boxenju, durfee}@eecs.umich.edu

One of the fundamental activities in multiagent systems is the exchange of tasks among agents (Davis & Smith 1983). In particular, we are interested in contracts among self-interested agents (Sandholm & Lesser 1995), where a contractor desires to find a contractee that will perform the task for the lowest payment, and a contractee wants to perform tasks that maximize its profit (payment received less the cost of doing the task). Multiple, concurrent contracts take place such that a contract may be retracted because of other contracts.

In our work, we are asking the question: What payment should a contractor offer to maximize its expected utility? If the contractor knows the costs of the agents and knows that the agent(s) with the minimum cost are available, then it can offer to pay some small amount above that cost. But the contractor usually will face uncertainty: it might have only probabilistic information about the costs of other agents for a task, and also about their current and future availability. A risk-averse contractor therefore needs to offer a payment that is not only likely to be acceptable to some contractee, but which also is sufficiently high that the contractee will be unlikely to retract on the deal as other tasks are announced by other contractors. A risk-taking contractor, on the other hand, may want to pay a little less and risk non-acceptance or eventual retraction.

This abstract defines the contractor's decision problem, and presents a contracting strategy by which the contractor can determine an optimal payment to offer.

The contractor's decision problem in the contracting process is to find a payment that maximizes its expected utility. The contractor's utility for the payment, ρ, is defined as $P_S \times U(Payoff_S(\rho)) + P_F \times U(Payoff_F(\rho))$, where $U(.)$ is the utility function, $P_{S/F}$ denote the probability of success *(S)* and failure *(F)* of accomplishing a contract, and $Payoff_{S/F}$ are the payoff of *S* and *F*, respectively, given ρ.

We have developed a four-step contracting strategy for the contractor to compute $P_{S/F}$ and $Payoff_{S/F}$ and thus to find the best payment to offer.

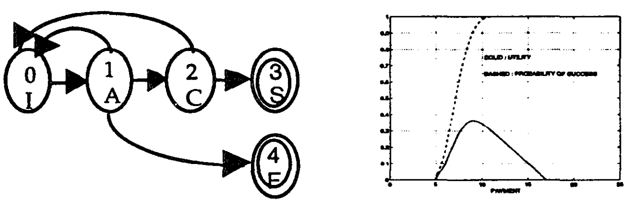
First, the contractor models the future contracting process stochastically as a Markov Process (MP). An example MP model is shown in Figure 1-(a). State *I* is the initial state, and state *A* is the announced state. State *C* is the contracted state, where the contractor has awarded the task to one of those who accepted its offer. State *S* and *F* are success and failure states, respectively. From *A*, the process goes to *C* if at least one agent accepts the offer. If no agent accepts the offer, the process goes to *F*. The process may go back to *I*, if there are some agents who can perform the task but are busy at the moment. If the contractee retracts the contractor's task (to do other more profitable task(s)), the process goes from *C* to *I*.

Second, the contractor computes the transition probabilities between the MP states. The transition probability from state *i* to state *j* is a function of many factors, such as the payment, the potential contractees' costs, the payments of other contracts, and so on.

Third, having the model and its transition probabilities, the contractor computes $P_{S/F}$ and $Payoff_{S/F}$. We have developed a theoretically-sound method of computing those values based on MP theory (Bhat 1972).

Finally, when $P_{S/F}$ and $Payoff_{S/F}$ are known, finding the optimal payment is an optimization problem. At present, the contractor uses a simple generate-and-test.

An example of a contractor's expected utility is plotted in Figure 1-(b). In this case, the contractor will receive the highest expected utility when it proposes a payment of 9.



(a) Markov process model (b) Expected utility vs. payment

Figure 1: A Markov Process Model

We have applied our approach to cases with two tasks, and are currently building a *m*-task model.

This research has been funded in part by Digital Libraries Initiative under CERA IRI-9411287.

References

Bhat, U. 1972. *Elements of Applied Stochastic Processes*: John Wiley & Sons Inc.

Davis, R., and Smith, R. 1983. Negotiation as a Metaphor for Distributed Problem Solving. *AI* 20:63-109.

Sandholm, T., and Lesser, V. 1995. Issues in Automated Negotiation and Electronic Commerce: Extending the Contract Net Framework. In Proc. of ICMAS-95, 328-335.