# Mobile Agents communication for knowledge representation

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**ABSTRACT**

The general structure of the paper is the following:

- We use the formalism of the Recursive Modelling Method for the purpose of decision theoretic calculations. The advantage of Recursive Modelling Method, when used for expected utility calculation, is that it is able to succinctly represent the content of the agents, including its preferences, abilities, and beliefs about the physical world, as well as the agents beliefs about the other agents, their preferences and abilities, their beliefs about the world and about other agents, their beliefs about others beliefs, and so on.

- We consider examples of various types of communicative acts. The results address the communicative acts that agents can use to share information about their environment (I call these modelling agents), acts used to express the current intention of the user (intentional messages), and acknowledging messages. We then present results on the agreement between the method of message selection and messages that humans choose, and show an experimental validation of our framework in a simulated multi-agent environment.

- Open problems and future work

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## 1 COMMUNICATION BETWEEN MOBILE AGENTS

The concept of mobile agent is defined in [1]. There are autonomous objects that migrate from node to node and provide to user which have executed themselves using database or computation resources of clients connected by the network. To migrate the mobile agent, it will be needed a virtual place so-called the mobile agent system to support mobility.

Our approach is knowledge-based and relies on a general purpose knowledge base (KB)( [2]), in this case implemented as a system of classes of objects and their instantiations. To facilitate effective communication, the agents has to include information about the possible states of knowledge, abilities and preferences of the other agent(s) present in the environment.

The need for considering the nestedness of the agents beliefs for communication has been widely recognized in the linguistics and AI literatures before ([8]), while research in cognitive science yielded evidence of nested mental models used by humans for purpose of communication. Clearly, without a model of the other agents mental states it would be impossible to properly assess the impact of a communicative act. With each communicative act we identify its decision-theoretic pragmatics, defined as the transformation of the state of knowledge about the decision-making situation the act brings about.

Imagine two agents engaged together in assembling a bicycle from parts scattered about a garage. A communicative act The front wheel is in the southwest corner of the garage, uttered by one of the agents, has the pragmatic meaning of changing the other agents beliefs about the location of the front wheel, if it did not know the location before. This act also changes the decision-making situation the agents are in: The other agent is now in the better position to get the front wheel and complete the bicycle assembly, and the time saved could be of benefit to both agents. The above communicative act, therefore, is endowed with both decision-theoretic pragmatics, as well as pragmatic meaning.

We now briefly describe a simple interaction between two agent, and present a compiled representation of a state of knowledge of one of them that we will use during further discussion of communication.

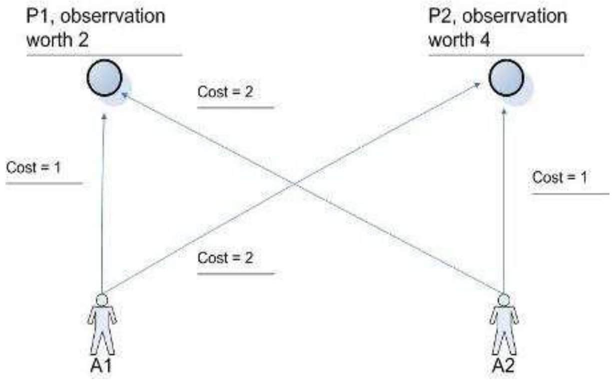



**Figure 1.** Description

We consider the example of interaction depicted in Figure 1. It involves two agents, A1 and A2, engaged in a common mission of gathering information. We take the perspective of A1 (A1 will be the speaker agent), who can detect two possible observation points, P1 and P2, allowing observations worth 2 and 4, respectively 5. Point P1 is closer to A1 and P2 is closer to A2, and the costs of getting to the points are assumed to be 1 or 2, as indicated in Figure 1. As we mentioned, this information resides in the agents general purpose KB. A1 has to make a decision as to whether to pursue the observation from P1 (well label this option a11 ), from P2 (a12 ), or do neither and just sit still (a13 ), and would like to do so in a way the maximizes the total value of information obtained by both agents, since its a joint mission, reduced by its own cost. We assume that these two factors are the only ones that determine A1 expected utility in this case. Note that the expected utilities of A1s actions depend what it expects A2 to do. If A2 observes from P2 then A1 is best off observing from P1 for the total payoff of 2 + 4 - 1 = 5, i.e, total value of observations minus A1s own cost. But if A2 decides to observe from P2 or do nothing at all, then its best for R1 to observe from P2. The expected payoffs of alternative behaviors of A1 can be assembled into a payoff matrix, and so on for A2.

In conclusion, I shall follow the steps :

- define the space of the recursive model structures.

  To handle the issue of predicting the other agents action, while the other agent attempting to do the same, we suggest a knowledge-based approach. Intuitively, instead of attempting to guess what the other agent will do, based on what its guess is as to what the original agent will do, etc., the agent should simply represent all of the information is has about the other agent, about what the other agent knows about the original agent, and so on. We argue that in realistic situations the information the agent has is finite and has to terminate at some finite level of nesting. Thus, the representation of this information is a finitely nested hierarchy of models that can be processed bottom-up.

For the purpose of the current example we assumed that the agent A1 knows that A2 has no information it can use to model A1. That means that the recursive model structure representing A1s decision-making situation in this scenario, terminates at the leaves with, what we call, no-information models. Thus, A2s lack of any information about A1 is represented as uniform probability distributions on the third level of the structure. They precisely correspond to A2s lack of knowledge about A1, since they contain no information about A1s action. The two models that A1 has of R2s decision-making situation reflect A1s uncertainty as to A2s being able to see point P2. In this case we assumed that A1, given the density of the foliage between A2 and P2, assigns a probability 0.1 to A2s being able to see through the trees, and a probability of 0.9 to it not being able to see P2. We call them modelling probabilities. In general, modelling probabilities are associated with alternative models, or branches, on any level of the recursive model structure. The bottom-up solution of the structure in Figure 2 amounts to computing the expected behaviors of agents given what they, in turn, expect of other agents. In the right branch, for example, given that A2 assigns equal probabilities of 1/3, the expected utilities of A2s actions can be computed as:

1/3(0 + 4 + 0) = 3/4

1/3(5 + 3 + 3) = 11/3

and 1/3(2 + 4 + 0) = 6/3,

for the consecutive alternatives. Thus, if A2 can see P2, its best alternative is $a_2^2$ to pursue the observation from P2. Analogous analysis of the other model shows that if A2 cannot see P2 then its $a_3^2$ is best and it will remain stationary. These two predictions can be probabilistically mixed with weights equal to 0.9 and 0.1 yielding an overall estimate of what actions A1 can expect A2 to perform, which will be called the intentional probability distribution, or the conjecture. In this case, the intentional probability distribution is:

$$p_{A2}^{A1} = [0, 0.1, 0.9]$$

where A1 is certain A2 will not pursue observation from P1, estimates that there is 10% probability that A2 will observe from P2, and that there is 90% probability that R2 will stay put.

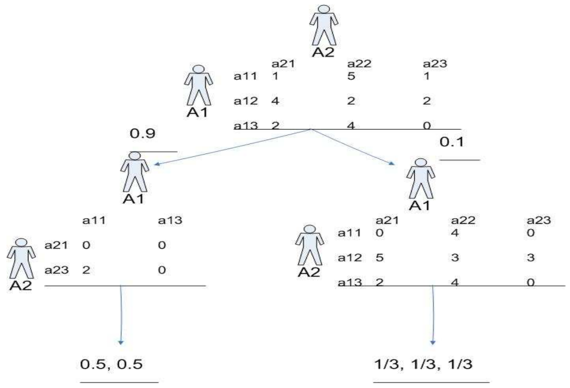



**Figure 2.** Recursive model

- representing the decision-making situation of the speaker agent, Ai.

Our modelling communicative acts update the hearers and the speakers model of the multi-agent world. The close correspondents of these type of communicative acts in speech act theory are the inform, assert, and tell acts. rational communication in multi-agent environments.

**Definition 1.1** *Modelling communicative acts are ones that contain information about the modelling probabilities, which represent Ais beliefs about the other agents in the environment.*

The modelling probabilities in the above definition are the probabilities associated with different models, or branches, in the recursive model structure.

Consider again the example of interaction depicted in Figure 1, and the recursive model structure representing A1s decision-making situation in this scenario in Figure 2. Assume, for the time being, that both agents can understand and generate communicative acts in English. Consider what would happen if A1 were to send a message, $M_1$, stating There is an observation point P2, twice as high as P1, behind the trees. Assuming that A1 estimates that the $M_1$ is certain to reach A2.

The projected structure can be easily solved, showing that A1 would be sure that A2 would observe from point P2, taking action $a_2^2$. Thus, the projected conjecture that A1 ascribes to A2 is $p_{A2}^{M_1;A1} = [0, 1, 0]$. The best alternative for A1 according to projected structure is to make an observation from P1, but the expected payoff has increased to 5. Thus, by sending the message $M_1$ to A2, A1 was able to increase the expected utility it gets from the interaction from 2 to 5. The utility of sending the message $M_1$ is $U(M_1) = 5 - 2 = 3$. This illustrates how our approach implements the fundamental function of communication, which is to confer some advantage to the speaker by influencing what the hearer knows and intends to do.

The above analysis assumes that A2 is guaranteed to receive and properly decode the content of A1's communicative act. However, it may be that A2 does not understand English, or that A1 used an unreliable communication channel. As we mentioned, A1's attempt to transmit the content above would then, formally, constitute a different communicative act, $M_{1.1}$. $M_{1.1}$ also has a different, although still well defined, DT pragmatics. Let us represent the imperfections in $M_{1.1}$ transmission by assigning a probability, $p_c$, to properly receiving and understanding the content of $M_{1.1}$.

Solving the projected structure in Figure 3 reveals that the intentional probability distribution describing A2's action is $0, 0.1{+}0.9p_c, 0.9{-}0.9p_c$. The expected utilities of A1's alternatives can now be computed as:

$u_{a_1^1}^{A1} = 1.4 + 3.6P - c$

$u_{a_2^1}^{A1} = 2$

$u_{a_3^1}^{A1} = 0.4 + 3.6p_c$

From the above we can see that, if $p_c > 1/6$, the value of the message depends on $p_c$ as:

$U(M_{1.1}) = 3.9p_c - 0.6$

If $p_c < 1/6$, A1 would prefer to choose a12 and observe from P2, with its payoff of 2. This is the same as without communication, so, if $p_c < 1/6$, the expected utility of is zero.

- define the set of the communicative acts agent Ai can perform.

We will assume for simplicity that this set is finite and it consists of alternatives generated, for example, by a communication planning module.

The elements of the set are communicative acts that differ in the content of the communicated information, but also differ in the way this content is encoded (the language used), and in the communication medium used for its transmission.

The purpose of intentional communicative acts is to inform other agents about the speakers current intentions. These acts loosely correspond to promise acts in the speech act theory, but they do not imply the notion of commitment. For example, an agent may inform another agent of its current intention to perform some action, but, say in view of newly acquired information, it is free to change its intention. Note, however, that it would be in this agents best interest to inform the other agent about the change of plans by sending another intentional message.

**Definition 1.2** *Intentional communicative acts contain information about the intentional probabilities*

$p^{Ai,Aj}_{Ak}$*, that represent Ais belief about an agent Aj expectation as to another agents, Ak, actions.*

In the simplest and most intuitive case, the speaker declares its own intentions and, in the above definition, Ai and Ak are the same speaker agent. In general, the intentional probabilities are conjectures the agents use to describe the expected actions of other agents.

For the purpose of the present discussion we assume that the truthfulness of these messages is guaranteed (as we mentioned the agents intentions may change, but it is in their best interest to inform others of such changes. Thus, a hearer can use an intentional message to predict what the speaker will do. In modelling the hearer, therefore, the speaker can truncate the projected recursive structure, because it knows that the hearers conjecture of the speakers actions correspond exactly to the content of the intentional message.

Let us take again the interaction in Figure 1, and suppose that A1 considers using a perfect communication channel to transmit a message I will observe from point P2 to A2. Let us denote this communicative act as $M_2$.

If A2 is not aware of the point P2 and receives $M_2$, it models R1 as pursuing its $a^1_3$ option doing something other than observing from P1 and so, for A2, the options $a^2_1$ and $a^2_3$ are equally good and equally likely. If A2 can see the point P2 and receives $M_2$, its options $a^2_1$ and $a^2_3$ are also equally good. Thus, the new overall intentional probability distribution over A2s options is $p^{M_2,A2}_{A2}$ . Now, the expected utility of A1s action $a^1_2$ increased to 3. The utility of $M_2$ is $U_{M_2} = 3 - 2 = 1$.

The above analysis assumes that A2 is guaranteed to receive and properly decode $M_2$. If the reliability of the communication used is characterized by the probability $p_c$ instead, the intentional probabilities A1 ascribes to A2 will be:

$p_c[0.5, 0, 0.5] + (1 - p_c)[0, 0.1, 0.9] = [0.5p_c, 0.1 - 0.1p_c, 0.9 - 0.4p_c]$

The expected utilities of A1s alternatives can now be computed as:

$u^{A1}_{a^1_1} = 1.4 - 0.4p_c$

$u^{A1}_{a^1_2} = 2 + p_c$

$u^{A1}_{a^1_3} = 0.4 + 0.6p_c$

Thus, the expected utility of sending this message over an unreliable channel is equal to the probability $p_c$.

# 2 AN APPLICATION WHICH USES COMMUNICATION BETWEEN MOBILE AGENTS

This section describes some of my experiments of coordination with communication in the air defense domain, in which two defense batteries have to coordinate their actions of intercepting multiple incoming threats.

First, I shall show that Recursive Modelling Method cases agrees with selections chosen by human subjects in four simple defense scenarios. Then, i shall show results of scaled up defense episodes in which agents perform slightly better than the human subjects.

The results obtained can improve effectively the problem of performance in communication between mobile agents.

In the simple scenarios below, we will consider optimal communicative behavior of Battery1 (triangle on the left in our scenarios) only, and assume that Battery2 is silent but can receive messages. Further, for simplicity, in all of the anti-air defense scenarios considered below Battery1 is assumed to have a choice of six communicative behaviors, generated by a communication planning module:

No Communication: No communication

M1: Ill intercept Missile A.

M2: Ill intercept Missile B.

M3: I have both long and short range interceptors.

M4: There is a missile A, whose position and warhead size are $P_A$ and $W_A$, respectively.

M5: There is a missile B, whose position and warhead size are $P_B$ and $W_B$, respectively. We wanted to investigate how RMM agents rank the messages in the above list, and whether there is an agreement between the communicative behavior advocated by RMM and human communicative behavior. As human subjects we used 32 CSE and EE graduate students. Each of them was presented with a scenario, and was given a description of what was known and what was uncertain in that scenario. The students were then asked to indicate which of the six messages was the most appropriate in each case, and which one was the second choice.

Consider the scenario depicted on the left in Figure 3. Here, the defense batteries face an attack by missiles A and B. A has a larger warhead size than B, but it is farther from the defended territory. The state of Battery1s knowledge before communication is summarized as a two-level recursive model structure on the left. Assume that Battery1 assigns the probability of to Battery2s being fully operational (having both long and short range interceptors and thus being able to target both missiles), and the probability of to Battery2s being incapacitated (in which case it cannot do anything). The remaining probability of is assigned to the No-Information model representing all of the possible remaining unknown cases. In this scenario Battery1 is assumed to have no more information. In particular, Battery1 does not know what action Battery2 expects of Battery1.

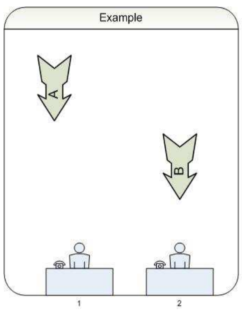
To compute the value of communication we solve both model structures and compare results. Before communication, Battery1 computes that if Battery2 is operational then the probability distribution over Battery2s possible actions A, B, and S is $[0.85, 0.15, 0.0]$. Using dynamic programming one can now easily compute that Battery1s best option is to shoot at missile A, with an expected utility $U_p(A)$ of 30.83.

After sending the message M1, the probability distribution over Battery1s actions at Level 2 is $[1, 0, 0]$. Thus, if Battery2 is fully operational, it will choose to shoot at missile B the probability distribution over Battery2s actions becomes [0,1,0]. This probability distribution is combined with the model of Battery2 being incapacitated and with the third No-Information model:

$(0.9 \times [0, 1, 0] + 0.05 \times [0, 0, 1] + 0.05 \times [1/3, 1/3, 1/3]) = [0.02, 0.92, 0.06]$

The resulting distribution is Battery1s overall expectation of Battery2s actions, given all of the remaining uncertainty. The combined probability distribution describing Battery2s actions is used to compute the expected utility of Battery1s action of shooting A.

The expected utilities of the other messages are computed analogously, and the results are shown in Figure 3. As expected, some of the messages have no value in this situation, and their computed expected utility is zero, since they do not convey anything useful and novel. Note that message M2 has a negative expected utility; it is a bad idea for Battery1 to announce its intention to shoot at missile B in this scenario.




| Messages | RMM U(M) | Human First | Second |
|---|---|---|---|
| No communication | 0 | 4 | 8 |
| M1: I'll shoot down A | 7.31 | 24 | 5 |
| M2: I'll shoot down B | -1.26 | 3 | 10 |
| M3: I have both ammo | 0 | 0 | 3 |
| M4: A-(7,3),500 | 0 | 1 | 1 |
| M5: B-(14,10),100 | 0 | 0 | 5 |

**Figure 3.** Results of the example

The results of human choices are also summarized in Figure 3. Twenty four, out of thirty two 75% of the subjects chose message M1 as the best in this situation, while five subjects judged it as a second best. This shows a considerable agreement between RMMs calculations and selections of the human subjects.

# 3 OPEN PROBLEMS AND FUTURE WORK

The following open problems arise from this paper:

- Comparative study concerning these modelling: compared the performance of the automated agents with that of communicating humans and showed that agents are more competent ([2]).

- Study the case when an mobile agent has toured for all nodes having no faults before that it does re-connect with the faulty nodes.

- investigate techniques that can be used to compile the results of full-blown Recursive Modelling Method into situation/communication pairs, to be used to urgent situations. This naturally gives rise to the establishment of protocols.

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