Modeling Agents and Interactions in Agricultural Economics

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ABSTRACT

When multiagent simulations are used for consensus building among stakeholders, it is important not only that the domain experts can deeply understand stakeholders' actual behavior but also that the stakeholders can feel the simulation result as their solution. To this end, we propose a modeling methodology which combines several techniques with the participatory method which takes stakeholders into the modeling process using role playing games (RPG).

There are two types of model required to simulate a social system as a multiagent system: agents (internal models) and interactions. Hence, we considered a modeling method according to each character. In modeling an agent (e.g. decision making) which is implicit in human, the identification of the model greatly depends on the modeler's ability. Therefore we propose a modeling method wherein classification learning creates an alternative model from RPG log data for validating the domain experts' hypothesis. On the other hand, in modeling interactions (e.g. negotiation) which are emerged outside of human, it is rather important to show and capture continuously appeared interactions. Therefore we propose a modeling method with participatory simulation where a stakeholder participates as an avatar and agents act as the other stakeholders in order to deeply understand the stakeholders' interactions. Our methodology was effective to give the domain experts a deeper understanding through a real case study of agricultural economics in the northeast of Thailand [17].

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent Systems*

General Terms

Design

AAMAS'06 May 8–12 2006, Hakodate, Hokkaido, Japan.

Keywords

multiagent simulation, participatory simulation, machine learning, agent interaction, modeling methodology

1. INTRODUCTION

Multiagent simulation has been used to analyze and design social systems (traffic [1], disaster management [6][11], market [14] etc.). The general modeling process is that a model created by the domain knowledge is adjusted to output the same kind of results as the real data. However, when using multiagent simulations for consensus building among stakeholders, it is important not only that the domain experts can deeply understand stakeholders' actual behavior but also that the stakeholders can feel the simulation result as their solution. In this paper, we aim to provide a modeling methodology to satisfy these points.

The participatory method by social scientists is suitable for this purpose [3][4]. The key idea is that stakeholders can understand the simulation result as their solution because they share the modeling process with the domain experts and can believe that the model reflects their actual behavior. A role playing game (RPG) where stakeholders play on a board representing their environment is used to share the modeling process and to well understand their actual thinking and behavior. "Participation" is the key aspect of our modeling methodology.

To simulate a social system as a multiagent system, two types of model are required: agents (internal models) and interactions. For example, in an economic system in agriculture described in this paper, decision making models and negotiation models of farmers and seed suppliers are required. Hence, we have to consider a modeling method according to each character.

In modeling an agent (e.g. decision making) which is implicit in human, the identification of the model greatly depends on the modeler's ability. Therefore, a method for model validation is very important. On the other hand, in modeling interactions (e.g. negotiation) which are emerged outside of human, it is rather important to show and capture continuously appeared interactions. RPG using a board in the participatory method is not enough to express such dynamic process as interactions, and it is important to give a method for this purpose.

In this study, to give solutions of each issue above, the following technological methods are applied in the notion of the participatory method.

Modeling agents with classification learning

A hypothesis of domain experts is validated by a model which classification learning creates from RPG log data. The merits are 1) classification learning creates an objective model without influence of the modeler's ability because the creation is based on the algorithm, and 2) classification learning is more robust than human in performance even when the number of elements to be compared is large. What is important here is to consider a method that classification learning creates a model which logically explains the stakeholders' behavior even if the data available is sparse (it is difficult to gather enough data for classification learning because of the cost of RPG).

Modeling interactions with participatory simulation

In participatory simulations, stakeholders participate as avatars and agents act as the other stakeholders. The merits of using this kind of simulation are 1) it is easy to express and record every interaction on a computer, and 2) domain experts can concentrate on a specific stakeholder because agents act as the other stakeholders. What is important here is to create an environment that supports the domain expert in designing agent-avatar interaction so as to elucidate the behavior of the stakeholder.

Our modeling methodology was actually evaluated in an actual case study of agricultural economics in the northeast of Thailand in co-project of IRRI[1] and CIRAD[2] [17].

The following section will first explain the related works. Section 3 will explain the agricultural economics used in our evaluation. Sections 4 and 5 will explain the modeling method of agents with classification learning and interactions with participatory simulations, respectively, using our example.

2. RELATED WORKS

Two studies have used machine learning with participatory simulation for modeling. 1) One applied machine learning to the logs of participatory simulations for developing diverse agent models in a virtual training system [12]. 2) The other allowed agents to learn effective negotiation strategies for the participatory simulations of a virtual market [9]. In these two studies, participatory simulation is not used to share the experience of domain experts and stakeholders. Moreover, machine learning is not used for validating a hypothesis of domain experts.

We know of two studies which use participatory simulation. 1) One developed a web forum of agents and stakeholders for holding a continuous RPG free from the constraints of time and place [4]. 2) The other used participatory simulations in which only humans participated as avatars so as to eliminate a drawback with the RPG approach in which roles of participants are fixed and emergence of new roles cannot be handled [5]. In the first study, participatory simulation is intended to create a place for continuous meeting of stakeholders and this differs from our use of participatory simulation: to exploit interaction models of stakeholders. The second also mentions design processes of participatory simulation, but they are not for constructing an environment where agents and avatar participate.

[1]International Rice Research Institute, http://www.irri.org/

[2]Centre de Coopération Internationale en Recherche Agronomique pour le Développement, http://www.cirad.fr/

3. AGRICULTURAL ECONOMICS OF NORTHEASTERN THAILAND

In this research, we applied our proposed processes to the agricultural economics of northeastern Thailand in a collaborative research project with IRRI and CIRAD [17].

The background is as follows. In the northeast of Thailand, the Thai government distributes a few different rice varieties. The problem is that the organization of this distribution is not always efficient: farmers do not always get the seeds they want while the seeds of some varieties are produced in excess. Also, it seems desirable that this distribution should not reduce the use of local varieties. The problem is how to develop a system that can both deliver good quality seeds and also conserve rice biodiversity. Researchers have been studying two subjects: 1) understand farmers' needs concerning rice varieties and the selection model of rice varieties and 2) to identify the problems of the current delivery system of rice seed by acquiring a farmer's selection model of seed suppliers and a flow model of rice seeds among the seed suppliers and farmers.

To realize this economic system in multiagent simulation, we need to have a) decision making model of farmers for rice varieties, b) decision making model of farmers for seed suppliers, c) negotiation model of suppliers for rice seeds and d) negotiation model of farmers for rice seeds. In this study, we will apply our modeling process of decision making and negotiation to b) and c), respectively.

4. MODELING AGENTS WITH CLASSIFICATION LEARNING

In this section, we will discuss the issues and the solutions in using classification learning to model agents (internal models) and explain the processes involved with an example: decision making of farmers for seed suppliers. The decision making model is represented in a decision tree and we selected the well-known decision tree learning algorithm "C4.5" for classification learning [13].

4.1 Issues

The characteristics as a classification learning problem are as follows:

1. The number of features tends to be large because the experts take into account all elements that they think might be related to the classification. However, the more features that are included, the more data sets tend to be needed to assure reasonable learning performance [10]. Unfortunately, it is difficult to gather enough data because the cost of RPG is high (an RPG session usually engages 12-15 players for 2 days).

2. Noise data can affect the learning result because the amount of data may be insufficient.

3. The classification knowledge gained through learning should logically explain the real behavior of stakeholders and satisfy the experts.

4.2 Approaches

In our approach for these issues, expert knowledge is effectively used for obtaining a model even from insufficient amount of data sets. Here, the unneeded features are winnowed in two ways:

Feature Selection Method

The wrapper approach[3] [10] is used for eliciting a model with higher classification accuracy for unknown data; that is, a model with more generality. This method identifies a feature subset that maximizes the prediction accuracy as determined by cross validation[4], by eliminating irrelevant features from the initial feature set through hill-climbing search. In this method, however, when the quantity of data sets is insufficient, there is a possibility that some features needed for adequately reproducing reality will be eliminated due to noise data. Therefore, in our approach, the features contained in the hypothesis (in a decision tree) are regarded as being candidates to adequately explain reality and retained in the process (e.g. five features in figure 2 are not eliminated in this process). These features are always contained in the feature subset, but the learning algorithm selects a part of features from the subset, so the important features are not always contained in the learning result. This means that the wrapper approach can winnow the features to prevent the learning from selecting irrelevant features which do not ensure generality.

Visualization Method

In order to obtain a result which logically explains the stakeholders' behavior, the learning model is refined by eliminating irrelevant features contained in it and applying the classification learning again. Such conditions are selected by the domain expert. Here, It is important to consider an evaluation method that gives domain experts intuitive understanding of the model and excludes their bias to the model. To this end, the environment and participants of the RPG are reproduced on a computer using a graphical interface and computer agents. The expert is shown the results made by the agents who have the learning model and the RPG log data itself (the expert is not told which is from the RPG log data). Then he puts comments to each result. After this, the model itself is directly shown to the expert. He selects irrelevant features, comparing his comments to the visualized result with the model.

There are three merits on this method. First, a visualized method helps the expert to find apparently strange results and eliminate irrelevant features. Second, the learning result can be neutrality evaluated, while the expert tends to criticize the learning result when the model is shown from the beginning because he is obsessed with his hypothesis. Third, he can scrutinize the learning result because a model is re-evaluated based on his comments to the visualized result. The reason why RPG log data is also shown to the expert is to convince him of validity of the learning result (he can accept a part of the learning result when the output of it resembles the one from the RPG log even if it does not support his hypothesis.).

[3]A method using a searching algorithm that identifies a feature subset which gives the best performance of a model outputted from an inductive learning. In many cases, cross validation is used to estimate the performance and hill-climbing is used to search a feature subset with the best estimated performance. In hill-climbing, there are two searching direction: one is backward elimination which begins at the full set of features and eliminates one feature which makes the estimated performance the best. Another is forward selection which begins at the empty set of features and adds one features which makes the estimated performance the best.

[4]Data sets are divided into n groups without overlapping. A machine learning program is applied to the n-1 groups and the result is tested by one unused group. The classification accuracy of the test data is used as criterion for the performance estimation. Switching the group used for the test data, this process is repeated n times. We assigned n to 10 which is the frequency generally used.

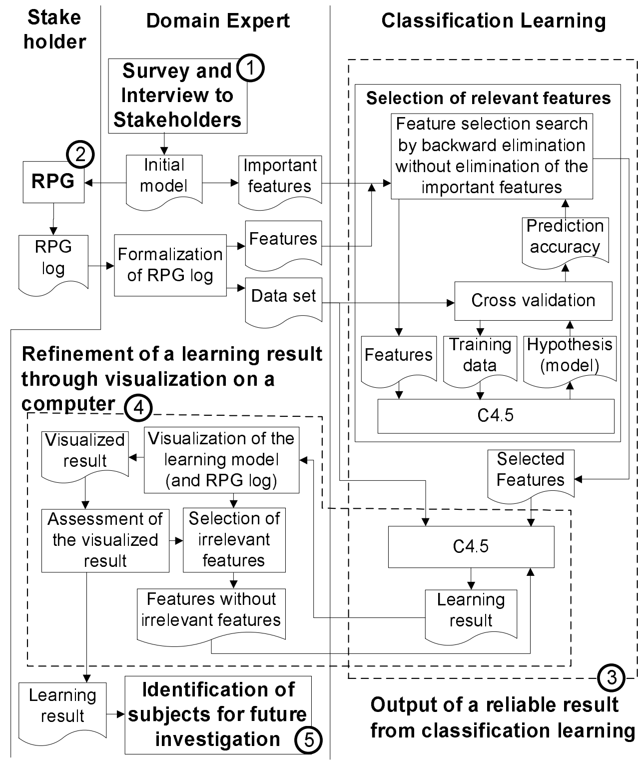


Figure 1: Modeling process for agents with classification learning

4.3 Modeling Process: a Real Example

We constructed five steps in which the approaches above are combined (Figure 1 shows the detail of this process); 1) Survey and Interview to Stakeholders, 2) RPG, 3) Output of a reliable result from classification learning, 4) Improving the result by expert knowledge and classification learning, 5) Identification of subjects for further investigation. This process will be explained with the results gained by applying it to a real example (see [15] for the detail explanation of the decision making model).

STEP1: Survey and Interview to Stakeholders

Domain experts create an initial model (decision tree) from relevant literature and interviews with stakeholders. Important features are extracted from the initial model. In our example, five features were extracted for the feature selection method (Figure 2).

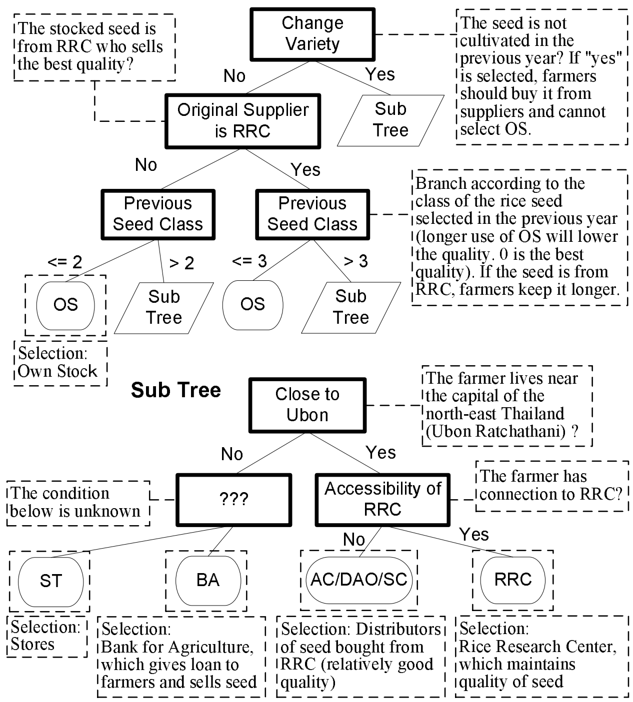


Figure 2: The initial decision tree model about farmers' selection of a rice supplier: The rectangles surrounded by bold lines are features. Five kinds of feature except "???" are the important one.

STEP2: RPG

RPG sessions using a board that represents the stakeholders' environment are organized. Log data for each stakeholder is recorded.

In our example, two RPG sessions were held. A board representing farm land was created (Figure 3 (a)). Totally, we got log data of 25 stakeholders.

STEP3: Output of a reliable result from classification learning

Learning data is created by transforming the RPG log data into a format that the learning algorithm can understand. Next, irrelevant features are eliminated by the feature selection method (mentioned in section 4.2). In this process, important features identified in STEP1 are not eliminated. Finally, the machine learning outputs a model from the feature subset and the data set.

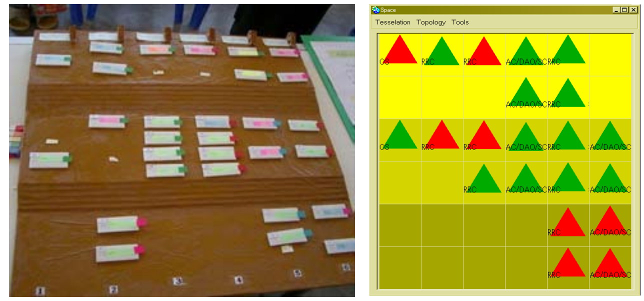
In our example, after formatting the log data, we had 16 features and 80 data sets. Next, the feature selection method was applied. Here, five of the features identified in STEP1 were not eliminated. Finally, the feature selection method eliminated 3 features and we got the first result from the remaining 13 features.

STEP4: Refinement of the learning result through visualization on a computer

The environment and participants are reproduced on a computer using a graphical interface and computer agents. In this evaluation, the experts are shown two types of results: results from the learning model and RPG data. After this, the model is directly shown to the experts. When there are irrelevant classification conditions in the model, the expert eliminates that feature which consists of the conditions and C4.5 will be applied with the resulting feature subset. This process is repeated until the expert is satisfied with the learning result.

We implemented the first learning model in CORMAS [2] (Figure 3 (b)) and evaluated the model by showing the results to the expert. At each step (equivalent to one year), the expert carefully observed the results and commented on the decision making of each agent.

After this, the first learning result was evaluated by directly showing the decision tree to the expert and an irrelevant condition was pointed by the expert (one feature was selected here and was eliminated from the feature set). The expert understood the reasons for the phenomena seen in the visualization. Classification learning was applied again with the reduced set of features. After applying the same processes in STEP4, the expert thought the learning result (Figure4) is logical to explain the decision making of the stakeholders in RPG and was satisfied with it, then we went to the next step.



(a) RPG board [17] (b) Visualized Interface

Figure 3: Interfaces for modeling: These are examples used in a case study of rice production in the northeast of Thailand. Both show upper, middle, and lower lands.

STEP5: Identification of subjects for further investigation

By comparing the experts' hypothesis (Figure 2) with the learning result, the experts investigated their hypothesis and find subjects for investigating in the future. These will be discussed among the domain experts or investigated by repeating the process from STEP1.

In our example, the expert found that some parts supported his hypothesis: a) A condition "Close to Ubon = yes" leads a branch by "Accessibility of RRC", b) The bigger value of "Previous Seed Class" leads not *OS* but *RRC* or *AC/DAO/SC*. Meanwhile, other parts did not support it and the following subjects were identified: a) The value of "Previous Seed Class" (2 or 3 in the hypothesis while 0 in the result), b) The importance of two features which contains in the hypothesis but do not contain in the result ("Change Variety" and "Original Seed Supplier is RRC"). c) The possibility of the other important features (there should exist several features for the decision of *OS* except "Close to Ubon = No").

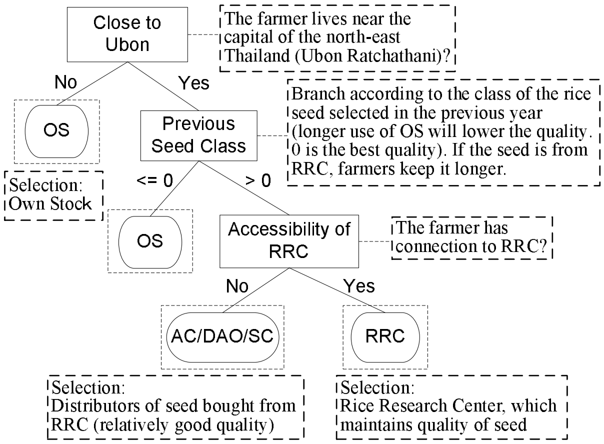


Figure 4: The final learning result

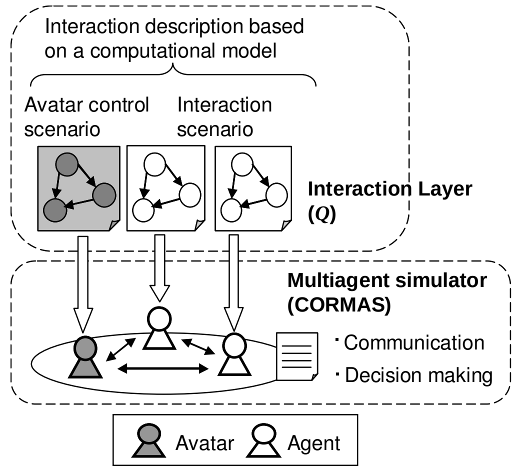


Figure 5: Agent Control from Interaction Layer

4.4 Evaluation

We can explain the effectiveness of our approach in the following way: first, the feature selection method reduced the cost of the expert refining the learning model. In our example, when the expert eliminates features without the feature selection method, it is necessary for the expert to iterate the refinement process three times, but when using the feature selection method, just one round of refinement was enough, because the feature selection method eliminated three features. In our approach, considering the preparation costs of the visualization method, it was desirable for the expert to reduce the refinement process. Moreover, we confirmed the effectiveness of our proposed method in which the features the expert thinks important are not eliminated in the feature selection method process. In our experiments, important features like these were often eliminated when this method was not used, and the experts could not explain the results as a decision making model of the stakeholders.

Second, we consider that using visualization to evaluate the learning model was useful for gaining a better understanding of the characteristics of the model and for facilitating the collaboration with the expert. The expert was able to make various comments about the decision making of agents who used the learning model because the interface had the same characteristics as the RPG. This is effective because it leads to more comments than when the learning model was shown directly to the expert, an approach that was tried in the early stage of our research.

5. MODELING INTERACTIONS WITH PARTICIPATORY SIMULATION

In this section, we will discuss the issues and the solutions in using participatory simulation to model interactions and explain the processes involved with an example: negotiation of seed suppliers. The negotiation model is represented in a state automaton and we implemented our participatory simulation in CORMAS/Q [16].

5.1 Issues and Approaches

Issues

For coaxing the actual behavior from stakeholders, it is important to design how the stakeholder controls an avatar and how agents interact with the avatar. Therefore, it is indispensable to give a development environment where domain experts are able to focus on designing interactions and the interaction design is directly used in system implementation. To this end, we developed a simulation system that uses the system architecture described in the next section.

Agent Control from Interaction Layer

We use a system architecture shown in Figure 5 where an interaction layer constructed outside of a simulation system controls the agents in the system[7][16]. This architecture makes it possible to use descriptions based on a computational model that makes it convenient to write interactions. Therefore, users can focus on interaction design.

As an actual simulation system based on this architecture, we combined the scenario description language Q [7] with the multiagent simulator CORMAS [2] which is often used in research based on the participatory method [3] (the system is called CORMAS/Q [16]). The computational model behind a Q scenario is an extended finite state automaton, which is commonly used for describing communication protocols. By using Q, users can directly create scenario descriptions from extended finite state automata. In Q scenarios, we can use sensing functions (cues) and action functions (actions). Scenarios are interpreted by Q interpreter, while cues and actions are executed by CORMAS. Cues/actions become the interface between domain experts and system developers, which enables collaboration in the design of interactions.

5.2 Interaction Description

For realizing participatory simulations where agents and avatars interact, it is necessary to assume the three kinds of interaction descriptions shown in Table 1. These descriptions are designed according to the modeling process shown in the next section. Interaction protocols are very important because they define the activity of avatars (stakeholders) in the simulation world. An interaction scenario regulates an agent's behavior about interactions (e.g. a negotiation

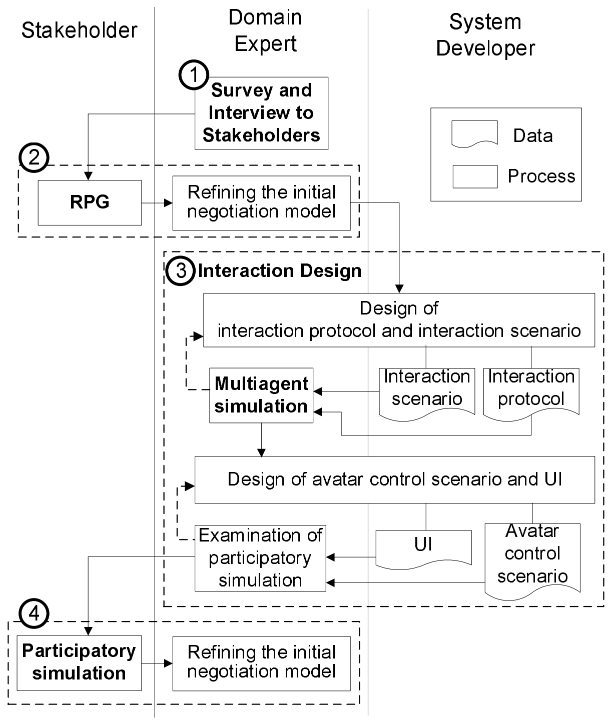


Figure 6: Modeling process for interactions with participatory simulation

model for agents who access the other agents and avatars). The avatar control scenario is an extended scenario of the interaction protocol. There are four elements in this scenario: 1) control of user interfaces (UI) (display etc.), 2) observation of input by a user through UI, 3) sensing from other agents, 4) action with other agents; this is triggered by input to the UI by a user.

Table 1: Interaction Descriptions

Classification	Definition of interaction description
Interaction protocol	Procedures which should be abided to negotiate with another agent or avatar
Interaction scenario (negotiation model)	Interaction procedures (e.g. access priority of trading or condition for completion of the deal) are described within the framework of the interaction protocol
Avatar control scenario	Control procedures of UI and an avatar along the interaction protocol

5.3 Modeling Process: a Real Example

The following four steps aim to refine an interaction model of a stakeholder and show a process to design three interaction descriptions shown in Table 1; 1) Survey and Interview to Stakeholders, 2) RPG, 3) Interaction Design, 4) Participatory Simulation (see Figure 6).

In this real example, we aimed to refine a negotiation model of *SC (Seed Center)* who is one of the important suppliers in northeastern Thailand. There are four types

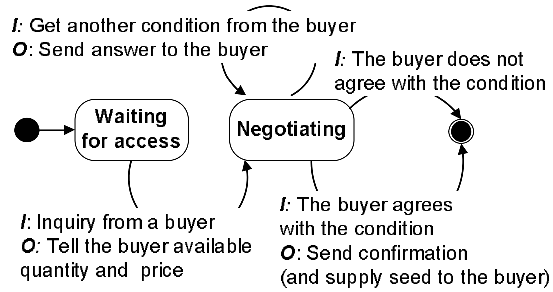


Figure 7: Example of interaction protocol (for sellers): Conditions are exchanged between the seller and the buyer in enough times to agree and the negotiation is settled if the buyer agrees/disagrees with the condition.

of supplier except SC and they are realized as agents in the participatory simulation (they are shown as A, B, C and D for descriptive purpose.).

STEP1: Survey and Interview to Stakeholders

Domain experts create an initial model from relevant literature and interviews to stakeholders. (In our example, the initial model was very abstract which just specified a contact list of each supplier).

STEP2: RPG

RPG based on STEP1 is held with stakeholders. In the process, RPG is very important because RPG is a good place for communication between domain experts and stakeholders unfamiliar with the research process and sometimes unfamiliar with computer systems. Through RPG, behavioral model and the reason behind the behavior are exposed. The initial model is improved by knowledge acquired through RPG.

The refined model of SC in our example is that rice seed is supplied according to a priority order (A, B, C and D)

STEP3: Interaction Design

An interaction protocol and interaction scenarios are described based on observation in RPG. What is important here is that several kinds of interaction scenarios are created for each agent to observe reaction of a stakeholder in participatory simulation. These descriptions are designed by a computational model of the interaction description through collaboration of a domain expert and a system developer. Finally, these descriptions are implemented in a computational language and tested through several runs of multiagent simulation. The processes of design and simulation are repeated until a domain expert is satisfied.

Next, UI and an avatar control scenario are designed by the domain expert and system developer for participatory simulation. In the avatar control scenario, the control procedures of UI are considered based on the interaction protocol. Next, UI and the avatar control scenario are implemented by the system developer and the participatory simulation system is tested by the domain expert. The processes above are repeated until the domain expert is satisfied.

In our example, through discussion between a domain expert and a system developer, an interaction protocol and

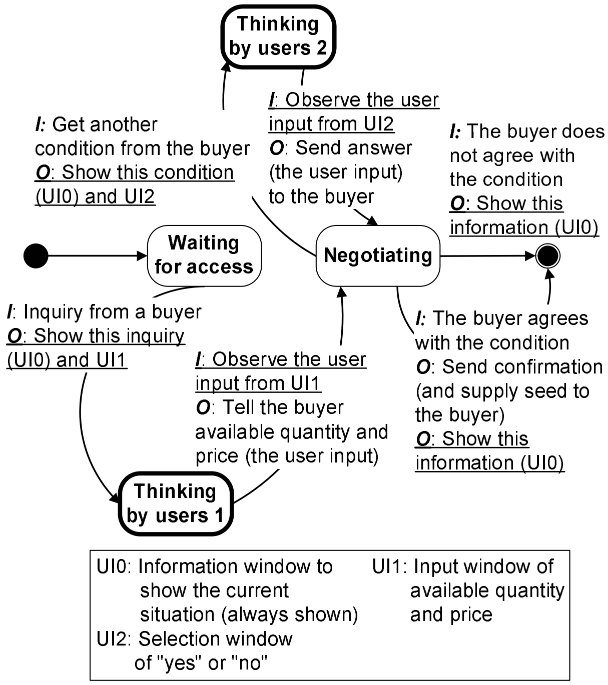


Figure 8: Example of avatar control scenario (for *Seed Center*): the interaction protocol shown in figure 7 is extended by putting controls concerning to UI (states surrounded by a bold line and conditions/actions with underlines)

interaction scenarios for each agent were designed by a state transition model which is a computational model of Q. The interaction protocol is shown in Figure 7. Three kinds of interaction scenarios are also prepared: a) access in a fixed order, b) access in a cheap price order and c) access in a short distance order. Next, the domain expert and system developer defined cues/actions of Q and the system developer implemented corresponding behavior of the cues/actions in CORMAS (this part of design process are described in [11]).

UI for our participatory simulation was not one big panel with all functions but small panels with only necessary functions at each scene, which are opened and closed according to the avatar control scenario. As in the interaction scenario, the avatar control scenario was designed by state transition diagram (Figure 8). Then, cues/actions are designed and corresponded to the control of UI or avatar behavior in CORMAS.

STEP4: Participatory Simulation

Participatory simulation with stakeholder is held. The domain expert refines the interaction scenario by analyzing the log data and knowledge acquired through conversation with the stakeholder.

In our example, the refining process of the model is as follows. The result after several times of participatory simulation was that supplier B was always selected first then the selection of A, C and D was not fixed. This was observed every time, though we changed the interaction scenario given to the agents in every run of simulation. After the domain expert recognizes this phenomenon, he tried one more around of simulation while he gave questions to the stakeholder. From the conversation with the stakeholder, the domain expert could refine the model as shown in Figure 9.

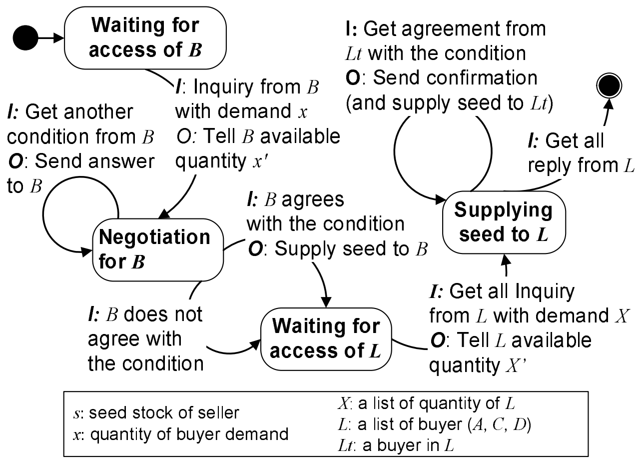


Figure 9: Refined negotiation model of *Seed Center (SC)* after Participatory Simulation: B is first chosen then A, C and D are equally distributed. If the stock remains, the other buyers will be supplied.

5.4 Discussion

We confirmed the merits to use participatory simulation. 1) The domain expert could focus on observing specific stakeholders (only *SC* in our example) because agents took roles instead of the stakeholders in RPG and a computer program automatically conducts the simulation. 2) The domain expert could give questions according to the progress of simulation. The stakeholder could monitor the simulation progress and see the impact of his own decision, which enabled him to give more concrete answer.

We consider that this participatory simulation operated as intended. This is because the system architecture could give the environment for the domain expert to focus on interaction descriptions and our proposed processes of designing three kinds of interaction descriptions were effective to reflect his knowledge acquired through surveys and RPG to the simulation world.

6. CONCLUSION

In this study, we proposed a novel methodology of modeling agents (decision making) and interactions (negotiation) in multiagent simulations for consensus building among stakeholders. This methodology combines several techniques with the participatory method, which takes stakeholders into the modeling process. We tackled the following two problems.

Modeling agents with classification learning

A modeling method wherein classification learning is applied to RPG log data was established for validation of domain experts' hypothesis (agent's internal model). The key ideas are 1) a feature selection method for enhancing reliability of the learning result by classification learning, and 2) visualization of the learning result on a computer to promote understanding of domain experts in refining the learning result. The modeling process with these methods was applied to farmers' decision model of seed suppliers. As a result, the domain expert's hypothesis was validated and several subjects for further investigation were found.

Modeling interactions with participatory simulation

A modeling method with participatory simulation was established for deep understanding of stakeholders' interactions (e.g. negotiation). The key ideas are 1) a system architecture where interaction layer controls agents gives an environment for the domain expert to focus on interaction descriptions, and 2) three kinds of interaction descriptions (interaction protocol, interaction scenario, avatar control scenario) are defined and designed through the modeling process. Actually, a participatory simulation was developed on CORMAS/Q [16] and the domain expert could get deeper understanding of a negotiation model among seed suppliers.

Our modeling methodology has the following two important features for multiagent simulations to build consensus among stakeholders. First, RPG and participatory simulation give shared experience of modeling with domain experts, which is important for stakeholders to find their solutions in the simulation results. Second, the modeling method with classification learning and participatory simulation enables domain experts to deeply understand and model stakeholders' actual behavior in the system. Indeed, the impact was confirmed in the real case study of agricultural economics in the northeast of Thailand [17].

In this study, we could use a decision tree and a state automaton to represent decision making and negotiation, respectively. In the other cases, however, we might find or develop suitable models, the learning algorithms, systems providing the interaction description. This will be the future works, which also give new seeds of artificial intelligence and multiagent research. Another future work is use of new technologies for user participation. For example, *Augmented experiment* [8] can give an environment where stakeholders take part in the simulation world from their real work space, which enables domain experts to understand more actual behavior of stakeholders.

7. ACKNOWLEDGMENTS

This research was supported by the young researcher development program of the JSPS 21st century COE program "Informatics Research Center for Development of Knowledge Society Infrastructure". We would like to thank Dr. Guy Trébuil and Dr. Chirawwat Vejpas who gave valuable comments as a domain expert, and farmers and seed suppliers who joined our experiment in Ubon Ratchathani.

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