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Unsupervised training of Multiobjective Agent Communication using Genetic Programming

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Abstract

Multiagent systems, in which independent software agents interact with each other to achieve common goals, complete distributed tasks concurrently under autonomous control. Agent Communication has been shown to be an important factor in coordinating efficient group behavior in agents. Most researches on training or evolving group behavior in multiagent systems used predefined agent communication protocols. Designing agent communication becomes a complex problem in dynamic and large-scale systems. The problem is further complicated in a multiobjective scenario. In order to solve this problem, in our previous research we had proposed a method applying Genetic Programming techniques, in particular Automatically Defined Function Genetic Programming (ADF-GP), to allow agents to autonomously learn effective agent communication messaging. For this research we take this approach further and combine multiobjective Genetic Programming in order to adapt the system to a multiobjective environment. In the proposed method separate agent communication protocols are trained for each objective. A software simulation of a multiagent transaction system will be used to observe the effectiveness of the proposed method in multiobjective environments.

1.Introduction

With the recent growth of need for faster and more reliable systems, interest has grown towards concurrent distributed systems. Multiagent systems, in which independent software agents interact with each other to achieve common goals, complete concurrent distributed tasks under autonomous control.

It has been shown in previous research [3][4] that agent communication is an important factor in coordinating efficient group behavior in agents. Most multiagent systems focus on the internal agent learning processes in achieving group behavior. [1][3][5] This assumes that the inter-agent communication is predefined and fixed, and the agents show intelligent group behavior by reacting to these communications appropriately. This leaves the agent communication design to be fixed by the implementor.

Designing efficient and effective agent communication protocols for a large-scale and complex multiagent system is difficult and time-consuming. Werner [2] has proposed a multiagent system where the system evolves a simple communication protocol.

In our previous research [6] we have proposed an approach applying genetic programming techniques, namely Automatically Defined Function - Genetic Programming (ADF-GP), to autonomously construct an efficient agent communication protocol in a single objective agent environment. Genetic Programming is a popular method in training multiagent behavior [3][7] and has been tested extendedly. This training method is easily extended to various problem domains, and does not require predefined training sets, thus is advantageous for training systems with complex and unknown solutions.

The problem becomes further complicated when applied to a multiobjective scenario. In a multiobjective environment, each agent may have several conflicting objectives to fulfill, and communication targets will most likely be different for each objective.

For this paper, we take the approach of our previous research [6] further, combining multiobjective Genetic Programming to our previous method and apply to multiobjective programming problems. In this case we define the multiobjective problem as a multiagent environment in which each agent has several conflicting objectives. In the proposed approach, separate communication programs are trained for each agent objective.

In Section 2 we first briefly describe the communication training method proposed in our previous research [6]. In Section 3 we describe our approach for applying the above training method to multiobjective agent environments. In Section 4 we describe the multiobjective Genetic Programming used in our proposed method.

A software simulation of a multiagent system modeling a marketplace was used to observe the effectiveness of the proposed method. The validity of the method was discussed by comparing the results of the simulation against previous methods.

2.Agent Communication Training using GP

Multiagent systems are generally regarded as being systems in which a group of autonomous agents interact to perform some set of tasks or satisfy some set of goals. The overall goal of most multiagent research is one of devising coordination protocols that allow a system of agents to behave in a coherent and convergent manner. It has been shown that agent communication is an essential factor for the emergence of cooperation in multiagents [3][4].

On the other hand by using a fixed communication protocol, the multiagent system loses its autonomy in defining its own communication capability. Also, by predefining the communication protocol, the multiagent system cannot accommodate dynamic changes in the environment requiring modifications or additions to the communication protocol.

In our previous research [6], a different approach to defining an agent communication protocol is proposed. By providing a method for the multiagent system to derive its own communication protocol, the agent system's autonomy will be protected and the flexibility of the system to adapt to changes in the environment will be increased. In this approach, the multiagent system autonomously defines its own agent communication protocol by applying GP techniques, namely Automatically Defined Function Genetic Programming (ADF-GP). With this method, the system designer does not need to have prior knowledge of the communication requirements for the problem domain, since the emergent communication protocol will be automatically tuned for the problem domain.

ADF-GP uses a 'divide and conquer' strategy to decompose a complex problem to smaller sub-problems and the individually solved sub-problems are recombined to provide the solution to the original problem. This approach can be more effective than using normal Genetic Programming to evolve a multiagent communication protocol, as each step in the communication protocol can be seen as a subproblem. By applying the ADF-GP approach, the communication contract syntax (i.e. the ADF sub-tree) can be separated from the actual implementation of each separate communication stage (i.e. the main GP tree), and both can be simultaneously evolved during the same training run.

Both the communication message handling program as well as the message construction program is created automatically by genetic programming. The messaging method is chosen from either a broadcast message or an agent-to-agent message by the GP. The message body, also created from within the GP, consists of a combination of message properties including message name string (e.g. message type), numerical value (e.g. cost), string value (e.g. item), and Boolean value (e.g. agreement/denial).

A homogeneous agent environment is used in which all agents in a particular environment are of the same basic type. A single communication protocol program is operated as a single GP chromosome, and a fitness value reflecting the efficiency or achievement of the communication protocol is used to compare the GP individuals.

Within each GP individual, two separate program trees, trained by genetic programming, were used for the single communication program. One tree was used by the agents when the agent needed to start an action (e.g. start to look for prospective agent clients). This program tree was processed when an agent's internal timer called the genetic program to start an agent action. The other tree was used by agents for receiving messages from other agents. This program tree was called as soon as an agent received a message, and the receiving agent could instantly take a reactive action to the message. Figure 1 shows the relationship between the receiving and sending message programs within an agent.

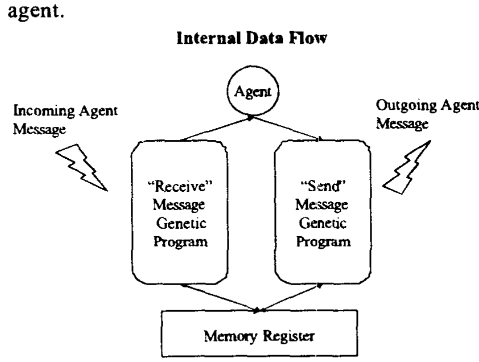


Figure 1. Internal Data Flow of Agent Messaging

3.Agent Communication in Multiobjective Environment

For this research we took the approach of our previous research [6] further, and combined multiagent Genetic Programming to the previous method and applied to multiobjective agent environments. Here a multiobjective agent environment is defined as an environment in which each agent carries several objectives to fulfill their goals. For example, a single agent in a virtual market may have three separate goals. One is to buy/sell (or make a contract) at the best price. Another is to buy/sell the most volume. Another is to buy/sell the best performing service or product. This could be defined as a multiobjective programming problem.

It is expected that by training separate communication program trees for each objective, it will allow effective communication to be trained for each separate objective. This is from the fact that by selecting the highest scoring transaction for each separate objective, this will ensure at least one Pareto optimal solution in the set.

Also, from previous research [6] it has been shown that an effective communication protocol can be achieved using genetic programming for a single-objective agent communication environment. Based on this result, if a multiobjective communication protocol can be separated to single objective communication protocols, then the communication protocol can be efficiently tuned for each objective.

The communicating agent will compare the different results (possible contract target agent) of the individual objective communication trees using a Pareto optimizing approach. From the resultant Pareto optimal solution set, a single contract target agent is selected using a predefined scalarization function. It is possible to train this scalarization function, but for the simplification of the problem, training of this function was not applied in the experiment. Figure 2 shows the message transfer using separate communication programs for each objective.

Agent Message Transfer Flow

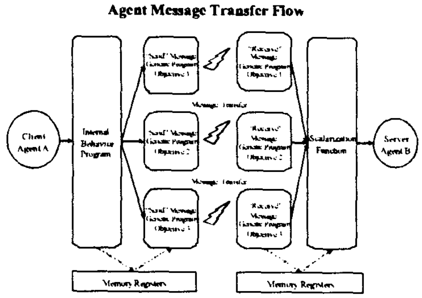


Figure 2. Message Transfer Flow for multiobjective agent communication

4.MultiObjective Genetic Programming

Compared with scalar optimization the objective nature of the multiobjective programming problem causes difficulties for the selection step of a GP. In the multiobjective case the main problem compared with the scalar case lies in the definition of the selection step. Other steps like mutation or recombination of alternative values need not be affected by the multiobjective nature of the alternative evaluations.

In the scalar case alternatives are judged by a single (real-valued) objective function which allows to define a linear order on the objective evaluations. With this, alternatives can be completely rank-ordered; a best alternative can be defined and so on. Canonical genetic programs then define probabilities of an alternative's reproduction based on its relative fitness. In evolution strategies usually an elitist selection strategy is applied which chooses the x best of the y children (comma strategy) or of the y children and x parents together (plus strategy) as parents for the next generation.

Considering a multiobjective evaluation of alternatives these and similar concepts cannot be applied since only a partial order (usually the Pareto order) is naturally defied on the objective evaluations.

A quite simple approach is to define a scalarization function that maps the q objective functions to a single aggregated value such that a single objective programming problem can be analyzed.

Modifications of the scalarizing concept have been proposed to allow a generation of a diversified set of solutions approximating the efficient set, for instance the usage of different scalar fitness functions, e.g. randomly one of the several objective functions in each selection step. Other approaches proposed use the Pareto order of the alternatives. Some of these approaches are based on pairwise comparisons, a kind of tournament selection, others consider the alternative set of the population in total. For instance, an alternative is judged by the number of other alternatives which dominate it.

For this research we applied multiobjective genetic programming to train the genetic program of the multiobjective agent communication program.

5.Experiment Results

A software simulation modeling a simple multi-client/multi-server modeling a marketplace was constructed to evaluate the proposed method. The agent community consists of two types of agents, client agents and service provider (server) agents. Many instances of each type of agent exist in the community. Each service provider agent may provide several different services, with different output efficiency (values). Each client agent requires one or more particular service, and its goal is to receive the necessary service from a service provider agent through some contract, and maximize the values for each of the several objectives.

The three objectives for a single agent in the virtual market are as follows. One is to buy/sell at the best price (lowest price for buyers, highest price for sellers). One is to buy/sell the most volume. One is for buyers to collect the best performing (value) service, and for sellers to collect the highest value return (income). For example, the cheapest product may not be the best performing, and with the provided cash, the buyer may not be able to collect much volume of expensive services.

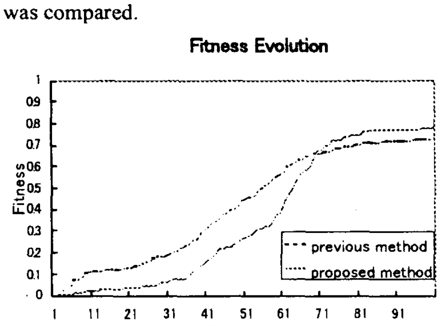
For this research we applied multiobjective GP to train the multiobjective agent communication program. The fitness of the GP individual was compared pairwise using a tournament selection, using Pareto ordering of the alternatives.

The types of service required by the clients and service provided by the servers, are changed every training cycle. The test was repeated for different number of agents, and service types.

The problem domain was restricted by using a homogeneous environment, which specified that all client and service provider agents trained a single common communication protocol, instead of each agent training its own specific communication protocol. This restriction greatly shortens the genetic programming training process, while still allowing the simulation to test for the validity of the proposed method.

Initially, the agent community starts with a randomly created communication protocol to carry out the necessary negotiations and trading of services. Each community is run the same number of communication steps in which the agents try to negotiate for services, after which the fitness of the community is calculated. The fitness is evaluated by the value of each objectives fulfilled, and reflects the satisfaction or achievement of these agents. Genetic operations are applied to the communication protocol program, favoring the communities with higher fitness values. This cycle of negotiation run and genetic operation is repeated until a specified number of cycles or fitness is reached.

The results of the communication protocol using only a single communication program for all objectives, and the proposed method using a separate communication program for each objective was compared.



Graph1. Fitness Evolution

6.Conclusion

In this research, an unsupervised training of multiobjective agent communication protocol using multiobjective genetic programming was proposed. Using the proposed method, emergence of a compact and efficient agent communication protocol for a multiobjective agent system was seen. The results indicated that the proposed method successfully trained the agents to dynamically construct a functioning communication protocol and work cooperatively as a group, without prior knowledge of the problem domain.

The proposed method focuses on the agent communication messaging, and shows that an efficient communication protocol can be evolved autonomously. This method implements learning on a different layer from agent learning methods which focus on the behavior patterns of agents, and is not expected to conflict with other behavioral learning strategies. Using the proposed method together with other behavioral multiagent learning methods, it is exptected to create a further efficient hybrid learning technique.

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