SITUATION IDENTIFICATION USING DYNAMIC PARAMETERS IN COMPLEX AGENT-BASED PLANNING SYSTEMS

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ABSTRACT
Survivability of multi-agent systems is a critical problem. Real-life systems are constantly subject to environmental stresses. These include scalability, robustness and security stresses. It is important that a multi-agent system adapts itself to varying stresses and still operates within acceptable performance regions. Such an adaptivity comprises of identifying the state of the agents, relating them to stress situations, and then invoking control rules (policies). In this paper, we study a supply chain planning implemented in COUGAAR (Cognitive Agent Architecture) developed by DARPA (Defense Advanced Research Project Agency), and develop a methodology to identify behavior parameters, and relate those parameters to stress situations. Experimentally we verify the proposed method.

1. INTRODUCTION

Survivability of multi-agent systems is a critical problem. Real-life systems are inherently distributed and are constantly subject to environmental and internal stresses. These include scalability, robustness and security stresses. It is important that a multi-agent system adapts itself to varying stresses and still operates within an acceptable performance region. Such an adaptivity comprises of identifying the state of the agents, relating them to stress situation, and then invoking control rules (policies). One of the fundamental problems is agent state (behavior) identification.

In this paper, we study a supply chain planning society called Small Supply Chain (SSC) implemented in COUGAAR (Cognitive Agent Architecture) developed by DARPA (Defense Advanced Research Project Agency), and develop a methodology for behavior parameter identification, and relating it to stress situations. The two important steps in our methodology are: 1. Identify the most discriminable behavior parameter set for situation identification, 2. Apply it to situation identification. To identify the most discriminable behavior parameter set we collect the time series data from one of the agents in SSC (TAO) and compute 38 statistical and deterministic parameters to represent the collected time series. In essence, these 38 parameters are the features of agent state. In our earlier work (Ranjan et al., 2002) we prove that SSC shows chaotic behavior from an inventory fluctuation point of view and computed chaos indicators (which we call as deterministic parameters without loss of generality). Though we compute 38 different parameters, next question we address is whether all these are really useful and necessary for identifying several stress situations. So, we develop a discriminability index and identify the most discriminable behavior parameter set based on this index as a representative parameter set for identifying several stress situations. Using those parameters we develop a nearest neighbor classification based method to identify stress situations.

2. SSC (SMALL SUPPLY CHAIN) SOCIETY

SSC is a COUGAAR society for supply chain planning composed of 26 agents. Each agent generates logistics plan depending on its relative position in the supply chain. TAO is an important agent of the SSC and we have selected it to test our schema. Figure 1 shows the detailed view. In TAO GenerateProjection Tasks are expanded to Supply Tasks, which are for internal consumption. Each Supply Task is expanded to Withdrawal Task, which is allocated to inventory asset. Supply Tasks are also transferred from other agents. They are expanded to Withdrawal Tasks, which are allocated to inventory asset. MaintainInventory Tasks, which are for the maintenance of inventory assets in TAO, are expanded to Supply Tasks. Each Supply Task is allocated to other agents.

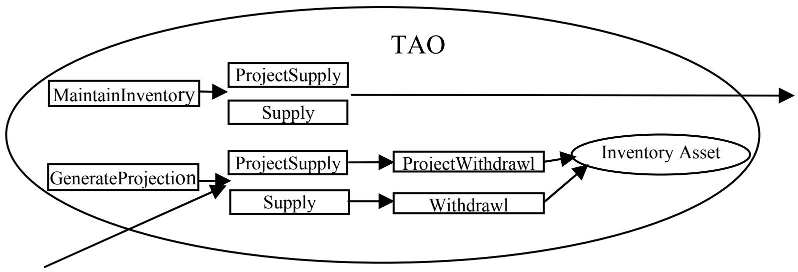

Figure 1. TAO in SSC

3. STRESSES AND BEHAVIOR

For the sake of analysis we have parameterized the stress situations and system behavior.

3.1 Stress

Stress refers to survivability stress and includes scalability, security, and robustness stresses. Scalability is defined as the ability of a solution to a problem to work when the size of the problem increases. And, survivability (regarding security and robustness) is defined as as the capability of a system to fulfill its mission, in a timely manner, in the presence of attacks, failures, or accidents (Ellison et al., 1997). There can be diverse stress situations, but in this paper we consider stress situations formed by two scalability stress types given below:

- Problem Complexity: Problem complexity is determined by the complexity of the planning task. This includes many aspects and we have chosen one of the stress types, called OpTempo of each agent. OpTempo defines operation tempo.
- Query Frequency: Each agent provides query service for its planning information to human operators. We have chosen query frequency (# of query request per second) to each agent as one of stress types.

Although SSC society is composed of 26 agents there are only 8 agents that are directly affected by OpTempo. We define stress levels: Low/Medium/High. So, the size of our stress situation space becomes 3^{34}.

3.2 Behavior

In SSC society an agent's behavior can be described by its Task groups' behaviors. Behaviors can be represented by time series. We define four different time series (Task arrival, Time to solution sorted by generation sequence, Time to solution sorted by completion sequence, and Queue length). A time series may be characterized using deterministic and statistical parameters as shown in Table 1.

Deterministic characterization makes it possible to handle non-stationary, non-periodic, irregular time series, including chaotic deterministic time series. In this study we use five different deterministic behavior parameters. In a deterministic dynamical system since the dynamics of a system are unknown, we cannot reconstruct the original attractor that gave rise to the observed time series. Instead, we seek the embedding space where we can reconstruct an attractor from the scalar data that preserves the invariant characteristics of the original unknown attractor using delay coordinates proposed by Packard et al. (1980) and justified by Taken (1981). Average mutual information has been suggested to choose time delay coordinates by Fraser and Swinney (1986). And, Schuster (1989) proposed nearest neighbor algorithm to base the choice of the embedding dimension. Local dimension has been used to define the number of dynamical variables that are active in the embedding dimension (1998). The most popular measure of an attractor's dimension is the correlation dimension, first defined by Grassberger and Procaccia (1983). And, a method to measure the largest Lyapunov exponent, sensitivity to initial condition as a measure of chaotic dynamics, is proposed by Wolf et al. (1985). We have systematically studied the use of the methods from the literature and computed 38 different behavioral parameters to characterize the four time series we have considered. These 38 parameters are shown in Table 1.

Table 1. Behavioral parameters

	Time Series			
	Task Arrival	Time to Solution (Generation)	Time to Solution (Completion)	Queue Length
Statistical Parameters	# of events Average Minimum Maximum Radius Variance	# of events Average Minimum Maximum Radius Variance		# of events Average Minimum Maximum Radius Variance
Deterministic Parameters	ami e_dim l_dim c_dim l_exp	ami e_dim l_dim c_dim l_exp	ami e_dim l_dim c_dim l_exp	ami e_dim l_dim c_dim l_exp

ami: average mutual information, e_dim: embedding dimension, l_dim: local dimension,
c_dim: correlation dimension, l_exp: lyapunov exponent

4. EXPERIMENTATION AND RESULTS

We ran several simulations of SSC to identify the most discriminable behavior parameter set.

4.1 Experimental configuration

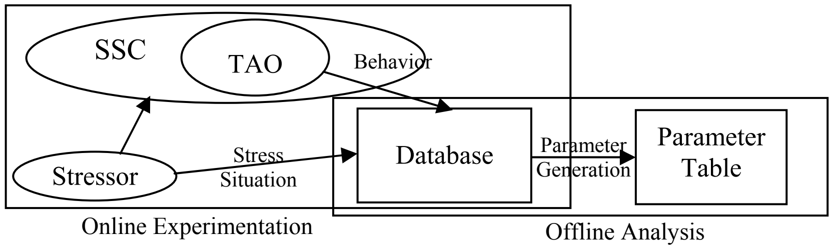

Figure 2. Experimental configuration

In this experimentation we store event data from TAO and the parameters of stress situation from stressor into an online database, and then from the database we construct the parameter table with stress parameters and behavior parameters as in the Fig. 2. The experimental matrix is shown in Table 2.

Table 2. Experimental matrix

TestID	OpTempo	Query	Repetition
PRE001	Low to all agents	Low to all agents	10
PRE002	High to all agents	Low to all agents	10
PRE003	Medium to all agents	Low to all agents	10
PRE004	Medium to all agents	High to all agents	10

4.2 Results

<u>Reduction of stress space</u>

Figure 3. shows an example of '# of events' parameter in each experiment repeated 10 times in four different stress conditions. We identified the stresses that have no significant effects on the society's behavior by comparing the behavior parameters under different conditions. The result shows:

- No significant difference between Low and Medium of OpTempo stress
- No significant effect of query frequency stress

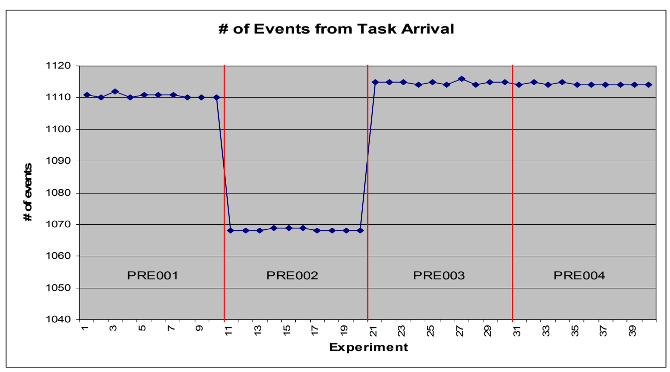

Figure 3. Comparison of a behavior parameter in different stress conditions

This leads to the reduction in the stress space to 2^8 (OpTempo Low/High for 8 agents) from 3^{34}.

<u>Discriminability of behavior parameters</u>

All the behavior parameters may not be equally good in helping the classification of stress situations. Therefore, there is a need for a measure of discriminating power of each of the behavior parameters. We call this as discriminability index (DI). DI can be represented as the ratio between sensitivity to the stress situations and random variation defined as:

$$\textit{Discriminability Index (DI)} = [\sum(\mu-\mu i)^2/n] \,/\, [\sum(si^2)/n] = \sum (\mu-\mu i)^2 \,/\, \sum (si^2) \qquad (1)$$

μ : Average of parameter values
μi : Average of parameter values from *i*th condition
si : Standard deviation of parameter values from *i*th condition
n : Number of conditions

We ranked those 38 behavior parameters using the DI. Top 5 are as shown in Table 3. As shown in the table '# of events' from task arrival time series was the most discriminable behavior parameter. Because this parameter is sensitive to the different stress situations and has small variation in the same stress situations the DI is relatively larger than those of other parameters.

Table 3. Discriminability index (DI) of behavior parameters

Rank	DI	Time Series	Behavior Parameter
1	2477	Task arrival	# of events
2	6	Time to solution	Variance
3	5	Time to solution	Radius
4	4	Time to solution	Average
5	4	Time to solution	Maximum

5. SITUATION IDENTIFICATION

Results from preliminary experimentation showed that '# of events' from task arrival time series (# of tasks) is the most discriminable behavior parameter in our stress space. So, assuming that the input to an agent affects the output depending on that agent's stress situation we can identify OpTempo of an agent by using four features of '# of tasks' as shown in Fig. 4.

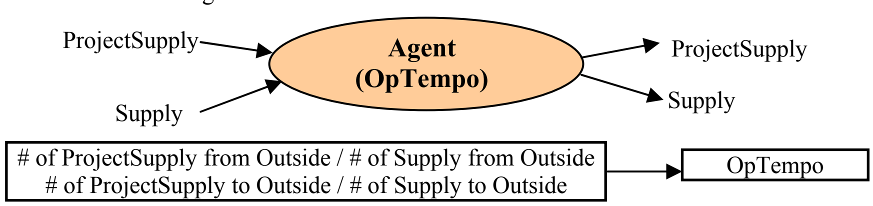

Figure 4. Features for situation identification

We performed an initial design of experiments and constructed a database of the behavior parameters from 100 experiments. Each agent's OpTempo is randomly chosen and the parameters are computed and stored in the database. Given a new experimental data we select the nearest neighbor from the base database by using the Euclidean distance between feature vectors. The stress level of the nearest neighbor is used for stress estimation. We estimated the stress level for 100 new experimental data using this approach. The results of estimation are shown in Table 4. Half of agents identified the stress successfully although the other half didn't.

Table 4. Stress estimation result

Stress	Correct estimation	Stress	Correct estimation
OpTempo of agent 1	54%	OpTempo of agent 5	100%
OpTempo of agent 2	100%	OpTempo of agent 6	94%
OpTempo of agent 3	56%	OpTempo of agent 7	53%
OpTempo of agent 4	100%	OpTempo of agent 8	46%

6. CONCLUSIONS

In this paper, we developed a methodology for extracting features from time series' of an agent-based supply chain planning society (behavior parameters) and relating it to stress situations. We identified '# of tasks' as the most discriminable behavior parameter of our 38 statistical and deterministic parameters in our stress space. Using this parameter we validated the method's ability to identify stress situation using nearest neighbor classification. Although our analysis showed deterministic parameters don't have the ability to identify stress situations in our stress space it is possible that they can be good indicators under other stress space such as security and robustness stresses.

ACKNOWLEDGEMENTS

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