International Journal of Fuzzy Logic and Intelligent Systems, vol. 4, no. 3, December 2004 pp. 277-282

An Approach to Generate A Theory of Coordination for Multi-Agent Systems

Eun Gyung Kim

School of Information Technology, Korea University of Technology and Education

ABSTRACT

This paper outlines our approach and the underlying design principles aimed at the generation of a theory of coordination. Such theory would assist in designing new Multi-Agent Systems(MAS) and provide trouble-shooting tools for suboptimally functioning MAS. This paper also describes the decisions that have been made in this endeavor. We have been able to show via a simplified model that approach is feasible and can produce results.

Key words : Multi-Agent Systems(MAS), Coordination Theory, Quality Measure of Coordination(QMC)

1. Introduction

There is currently much interest in agent societies, following the early work on naturally occurring cooperative systems (biological and economic) and on Distributed Artificial Intelligence (DAI) since the 1980s. The field is mature enough to benefit from solid theoretical foundations for coordination. However, coordination theory is currently ad hoc and amorphous, in that there is no unified model of coordination, though there exist many constructs describing specific phenomena in DAI and MAS. With the impending advent of large-scale agent-based societies, there is a need for theories that builders can use in designing such societies, instead of being forced to learn from trial and error every time such a society is built.

Social structures may enhance the coordination of agent activity, such as message management, and the allocation of resources and tasks. Such structures are alliances, coalitions, teams and markets of which only the first grouping is considered for the time being. The structures are external to and independent of individual agents, and would allow the scaling-down of complex systems consisting of large number of agents. By reducing the danger of combinatorial explosion in dealing with the problems of agent cognition, cooperation and control, we expect to be able to manage the emergent behavior of individual agents and of alliances of agents.

Cognitive activities, such as decision making, plan generation and execution, are usually performed jointly by groups of agents relying on distributed knowledge, skills and resources. There is a single group to deal with and to respond to, instead of an indefinitely large number of individual agents. This mode of operation leads to higher efficiency as well as to the possibility of graceful degradation; i.e., whenever a small number of operating units become dysfunctional, other units can take over their responsibilities while the whole system does not crash but produces useful results, perhaps at a slower pace and of lower quality.

It will be helpful to provide a precise definition of emergent phenomena since its interpretation varies in different disciplines. The term refers to the appearance of patterns (of properties, actions, results, information, knowledge) that are not apparent at lower levels. Individual agents and groups of agents may well be aware of the possibility of emergence and could strive to enhance or to diminish it and its effects. We can talk about a reasoning horizon within which agents can predict emergent phenomena and their effects. A usually more limited domain is the control horizon within which the agents can successfully influence higher level events by lower level activity. This paper considers only the control horizon. Notice that the formation of group of agents, the actions jointly decided upon and the norms are emergent phenomena because they are not under the control of individual agents.

2. Coordination

Coordination has been defined as "the process of managing dependencies between activities" [1]. Its fundamental components are the allocation of scarce resources and the communication of intermediate results. Coordination is needed and is usually available also in those cases in which there is no full cooperation among the agents or group of agents. In a human society, for example, competition is constrained by consumer protection, various government agencies and anti-trust laws. People and organizations antagonistic to one another may interact via prescribed legal channels. Coordination theory can be defined as the set of axioms, constructs and analytical techniques used to create a model of dependency management in MAS.

Manuscript received Dec. 2, 2003; revised Sep. 8, 2004

3. On the Generation of A Theory of Coordination

Validation and verification of state space models, based on emergent variables, will be done using the simulation model of a representative MAS. The planned environment for our experiments, the P-System (P stands for production), represents a metaphorical and abstract version of an earlier system, the Distributed Control of Nationwide Manufacturing Operations system [2,3,4]. The P-System shares characteristic properties with most MAS and is used for a series of statistically designed experiments. In the course of running the P-System under different conditions, we observe and measure data from which certain high-level, emergent variables can be created. This paper infers, from the statistical analysis of the data, characteristic and important descriptors of the organization and functioning of MAS. It is expected that the resulting relationships between the evaluated observations and the respective properties of the agent societies may produce a satisfactory theory of coordination, which in turn would generate design tools and guidelines for the construction of new MAS, and trouble-shooting tools for analyzing existing MAS.

We hope that the theory being developed will help in understanding coordination in general, as well as from the basis of models of coordination for specific applications. This paper notes that related empirical work has been done by several researchers, such as the pioneering projects on the evolution of cooperation by Axelrod and associates [5].

The P-System creates the following environment:

1) Communication between agents is asynchronous and over limited bandwidth. It includes request for information, resource or action; task or resource allocation to agents; a piece of information; an acknowledgment; etc. Messages can be broadcasted at large, or sent to selected groups of agents or to an individual one on the basis of need-to-know and qualified-to-know.

2) The sequence of manufacturing operations of a given product defines a hierarchical network of tasks, the P-tree, which corresponds (is homomorphic) to the problem solving network needed by the planning process (see Figure 1). Although the top layer of the P-tree is an AND-tree, each node can also be associated with an OR-subtree (alternative tasks can accomplish the given job at the respective process node). Leaf nodes references raw materials or sub-components provides by other producers. Higher-level process nodes correspond to manufacturing/assembly operations.

3) Planning is equivalent to assigning the (metaphorical) manufacturing/ assembly operations to resources over space and time. An agent with a higher-priority task (see below) can obtain a needed resource from another agent with a lower-priority task. The latter task is performed with a less satisfactory resource (more expensive or slower) or preempted until the loaned resource is returned.

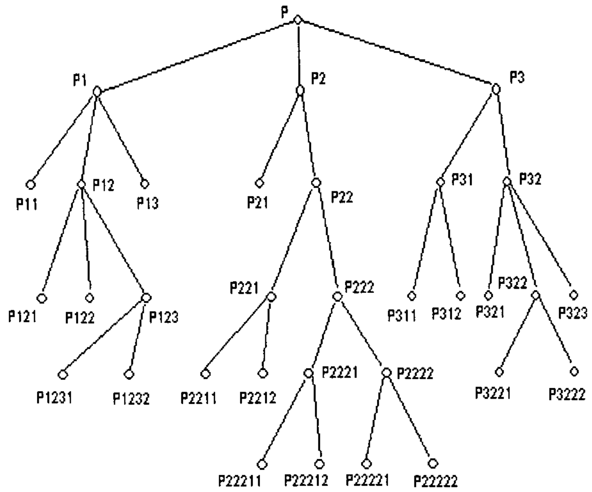

Figure 1. The metaphorical production tree, the P-tree

4) Resource availability (tools for the assembly/manufacturing operations) may change intermittently or regularly. Idle allocated resources and the (temporary) storage of components also cost money. The total range of resource availability has four subranges: (a) infeasible the production process cannot function for lack of indispensable resources; (b) deficient the production process can function only if some resources are transferred between process nodes at opportune moments (balancing the costs of transfer and component storage); (c) scarce some tasks must be allocated suboptimal resource types; (d) abundant every task can be allocated the optimum resource type.

5) Tasks may be priority-oriented or deadline-oriented. The former implies that each task associated with the completion of a component must be well-coordinated with the completion of its sibling, ancestor and descendent components. Tasks in the deadline-oriented category have a deadline by which they have to be performed to satisfy the completion constraints of the final product.

6) There are three tiers in resource taxonomy: (a) *r*esource category (every item in a category can be used for one or more tasks); (b) a resource category contains one or more resource types(a given task can be performed at different cost or time levels, depending on the type chosen); (c) one or more resource instances exist within each resource type these are the ones actually allocated to tasks.

7) Agents are associated with each process node, resource category and resource type, are spatially and functionally distributed, assume different levels of autonomy and different capabilities in network perception (for reactive behavior), modeling other agents and the environment (for predictive behavior), maintaining network coherence, communication and

negotiation, short-term and long-term planning, adherence to different coordination and cooperation regimes, plan generation and execution for time-critical tasks. 8) Two objective functions can be used: the P-System is to produce a given number of final products either (a) at a minimum cost within a given period of time, or (b) at a given cost within a minimum period of time. Both of these require an optimum allocation schedule of the manufacturing/assembly operations and resources to individual agents over space and time, while satisfying a set of constraints.

9) There are Manager Agents with different responsibilities. A top-level Monitor Manager collects and processes information from the other Managers, and stores it in a knowledge base. The Message Manager intercepts each message, records the IDs of the agents that originate, transmit and receive it, as well as categorizes and stores them according to their contents type in a Message Database. (This is crucial for the development of the trouble-shooting tool.) The Coordinative Process Manager is concerned with solution synthesis, reinforcement (such as the support in the coordinator-coworker relationship), and scheduling processes (tasks and resources). The Manager of Negotiating Processes assesses how agreements and decisions are made and kept. The Manager of Neutral Processes observes the cost and the effect of learning processes. The Constraints Manager identifies the cost/benefit ratio of inherent and imposed constraints (capabilities, classes, timing, costs, capacities, resource availability). The collected information is processed by the Statistical Analyzer Manager.

In order to attain a high-level of generality, we have originally defined 25 control variables (CVs) that characterize tasks, agents, resources, skills, production processes, relative cost functions, events and constraints. For each experiments (a run of the P-System), particular CV values are automatically selected by the Experimental Design Generator according to a multi-tier, balanced, incomplete, factorial design (see section 4.2).

4. Empirical Explorations

Significant effort has been spent on identifying a reliable but combinatorially not explosive technique to obtain results that can show the method of computation and prove the feasibility of the approach. This paper lists some of the decisions made along this line.

4.1 The Quality Measure of Coordination (QMC)

The metaphoric model of the manufacturing/assembly operation in the P-System is optimally coordinated if subcomponents arrive at every process node simultaneously and at the required rate while the total production cost or time is minimized and the total production time or cost, respectively, is kept under its allowed level. This leads to our definition of the Quality Measure of Coordination (QMC), based on the concept of synchronization and supply balancing,

$$QMC = \frac{\sum_{(l)} l.\ \sum_{(j)} t_{lj}^{*}/t_{lj}}{\sum_{(l)} \sum_{(j)} l(j)}$$

Here l is a level number, l(j) references the level where the j-th node is, t_{lj}* is the best possible time associated with assembly/manufacturing at node lj (the j-th node at level l), t_{lj} is the actual time used after local and global optimization (these terms refer to systematic resource exchanges when needed). The weighting factor in the numerator, l, expresses the fact that deficient synchronization and supply balance has a detrimental, cascading effect on coordination at the levels above the process node in question. (The lower the node level, the worst the effects are.) The denominator normalizes QMC to the range [0,1].

The optimization of QMC under different conditions and its relationship to judiciously chosen functional combinations of CVs, the emergent variables, play a central role in this research.

4.2 The Statistical Experiment Design

CVs determine the functional and operational characteristics of the P-System and produce emergent behavior. The emergent variables, one or a combination of a few CVs, represent the aspects noted before. Some CVs are categorical variables of qualitative nature; e.g., whether resource allocation is preplanned or reactively performed during the run of the P-System. Most CVs are, however, quantitative. The expectedly relevant CVs belong to one of the following groups: 1) skill-related, 2) resource-related, 3) task-related, 4) agent-related, 5) inventory-related, 6) production- related, 7) event-related, 8) constraints-related (identity, capability, class, capacity and temporal). To develop a demonstration system, we have drastically reduces the number of CVs to 12. These are resource-, task- or inventory-related. We have also left out all event- and agent-related CVs, and postponed the study of reactive planning and message traffic until later.

The statistical design of experiments needs some novel ideas. The design process consists of two phases. The first phase deals with a subset of the Total Number of Qualitative Designs of experiments, TNQD, called NQD. We identify five equally-sized qualitative subranges of the total quantitative range of each CV: very low, low, medium, high, very high. Thus, if TNQD = 5^12 (there are 12 quantitative CVs currently), an arbitrary subset of this can be obtained by generating NQD random numbers between 1 and TNQD, each pointing to a qualitative design selected. (This heuristic must be used since there are no symmetrical, balanced, fractional experimental designs available for such high number of control variables.) The second phase of this design process leads to actual quantitative computer-based experiments. Every qualitative design obtained in the first phase is used to carry out a sufficiently large Number of Quantitative Experiments (NQE); i.e., runs of the P-System. We assign randomly chosen quantitative values to each CV within their respective current qualitative subrange. The QMC values are computed while the objective function can be minimum total time or minimum total cost. This approach assures a high level of generality in the findings.

In order to obtain optimum precision in the results, given the total length of computing time, how much time should be spent in considering different qualitative designs and how many quantitative experiments should be performed for each qualitative design. An interesting heuristics leads to the meaningful ratio between NQD and NQE. The basis of the heuristics is that the total variance of the resulting QMC values is made up of three components - the first one is due to the different qualitative designs selected, the second one is due to the different actual quantitative experiments that belong to the same qualitative design, and a third one is a random scatter not related to ant manageable factor. The calculation of the first two components is now explained by the following example. Assume that we have NQD = 4 (four qualitative designs are selected) and NQE = 3 (each qualitative design has three actual quantitative experiments associated with it). In the following Table 1, QMC is denoted by Q.

The variance due to different qualitative designs is Var(QD) = Var(Av(Q_{ij})), which is the variance of the items in the third column. Further, the variance due to different quantitative experiments is Var(QE) = Av(Var(Q_{ij})). The ratio Var(QD)/ Var(QE) should be the ratio of the times allocated to QD and QE, respectively - the idea being that the larger the variance of an item is, the more time should be spent on its measurement.

Table 1. How to divide up total processing time

Qualitative Design	QMC Values in Quant. Experiments	Avg. of QMCs	Variance of QMCs
1	Q_{11}, Q_{12}, Q_{13}	Av(Q_{1j})	Var(Q_{1j})
2	Q_{21}, Q_{22}, Q_{23}	Av(Q_{2j})	Var(Q_{2j})
3	Q_{31}, Q_{32}, Q_{33}	Av(Q_{3j})	Var(Q_{3j})
4	Q_{41}, Q_{42}, Q_{43}	Av(Q_{4j})	Var(Q_{4j})

4.3 Miscellaneous Decisions

In order to run the P-System, we had to decide on the number of final products (NFP) first to be produced by the P-System in the experiments while QMC having a fairly steady value beyond NFP. There are several factors that may cause difficulties in this regard. Such are the "running-in" and "running -out" times for the P-System. During the former period, the assembly/manufacturing operations start at the bottom of the P-tree and gradually reach its root from where the first final product leaves. From this point, the P-System works continuously and the completion rate of the final product should be constant. Similar issues arise during the running-out phase when node activity gradually disappears from the bottom of the tree upwards. We have found that continuous and steady production is experienced after the first three final products leave the root of the P-tree; thus NFP = 4 was chosen. It is important to characterize each member of the set of experiments by the Resource Availability category it belongs. We can then make relevant conclusions concerning the effects of less than abundant resources - the infeasible, deficient and scarce cases - on production time and cost aspects.

5. The Computational Approach

Having identified the ratio r = Var(QD)/Var(QE) ≈ 60, we specified NQD = 11,000 (out of which 2,400 qualitative designs proved to be in the Infeasible Resource category). Instead of the "expected" NQE = 871,200, we obtained 860,282. In addition to the 12 CVs considered in the experiments, the successfully completed experiments were also assigned a value of the categorical variable RA (Resource Availability) as deficient=1, scarce=2 or abundant=3. The average execution time of a quantitative experiment was 334.51 ms and the size of the output file was 61.8 MB.

Table 2 describes the currently used list of CVs, the RA and QMC, their notation (the x's), and their role in the P-System. We emphasize that the reduced set of independent variables is not sufficient to produce acceptable results because of their numerous latent relationships among themselves and with the dependent variable QMC. As stated before, our major objective in the work described is to prove the feasibility of our approach.

The Principle Component/Factor Analysis program and other parts of the SPSS statistical package have produced, among others, the following relevant results: 1) A 14*14 Correlation Matrix of the 13 independent variables and QMC. 2) Six factors, F's, linear combinations of the x's, have zero correlations among themselves and high correlations with QMC. 3) A series of regression functions, models, that connect MQC, on one hand, and - via the F factors - the x variables, on the other. The final, 24-th model, chosen by us, has the highest number of terms, 24, each with statistically significant correlation with QMC and no cross-correlation among the terms.

Table 2. The dependent variable, the independent variables and their function

Variables	Notation	System Function
CV1	x_1	Number of Resource(Res.) Categories
CV2	x_2	Number of Res. Types per Res. Category
CV3	x_3	Number of Res. Instances per Res. Type
CV4	x_4	Cost of Res. Type working per task difficulty and per unit time
CV5	x_5	Time necessary for Res. Type to accomplish work per task difficulty
CV6	x_6	Time necessary to transfer a Res. Instance between two process nodes
CV7	x_7	Cost necessary to transfer a Res. Instance between two process nodes
CV8	x_8	Number of Task Categories
CV9	x_9	Number of Task Types per Task Categories
CV10	x_{10}	Number of Skills OR-ed per Task Type
CV11	x_{11}	Storage cost per subcomponent piece per unit time
CV12	x_{12}	Maximum storage size
RA	x_{13}	Resource Availability (categorical variable)
QMC	Q	Quality Measure of Coordination

The six mutually orthogonal factors "explaining" the QMC are:

$F_1 = b_1 + b_2.X_{13} + b_3.X_3$ $\quad b_1 = 0.736,\ b_2 = 0.123,\ b_3 = -0.017,$
$F_2 = b_4 + b_5.X_2 + b_6.X_1$ $\quad b_4 = 0.891,\ b_5 = -0.471,\ b_6 = -0.010,$
$F_3 = b_7 + b_8.X_5$ $\quad b_7 = 0.775,\ b_8 = -0.004,$
$F_4 = b_9 + b_{10}.X_{11} + b_{11}.X_8$ $\quad b_9 = 0.773,\ b_{10} = 0.009,\ b_{11} = 0.003,$
$F_5 = b_{12} + b_{13}.X_9$ $\quad b_{12} = 0.778,\ b_{13} = -0.016,$
$F_6 = b_{14} + b_{15}.X_7$ $\quad b_{14} = 0.775,\ b_{15} = -0.004.$

The Regression Function of Model 24 is accepted as:

$$Q = a_0 + a_1.F_1 + a_2.F_2 + a_3.F_3 + a_4.F_4 + a_5.F_5 + a_6.F_6 + a_7.F_1\text{^}2 + a_8.F_2\text{^}2 + a_9.F_3\text{^}2 + a_{10}.F_4\text{^}2 + a_{11}.F_5\text{^}2 + a_{12}.F_6\text{^}2 + a_{13}.F_1.F_2 + a_{14}.F_1.F_3 + a_{15}.F_1.F_4 + a_{16}.F_1.F_5 + a_{17}.F_1.F_6 + a_{18}.F_2.F_3 + a_{19}.F_2.F_4 + a_{20}.F_2.F_5 + a_{21}.F_2.F_6 + a_{22}.F_3.F_4 + a_{23}.F_3.F_5 + a_{24}.F_3.F_6 + a_{25}.F_4.F_5 + a_{26}.F_4.F_6 + a_{27}.F_5.F_6$$

with

$a_0 = 0.784$, $a_1 = 0.161$, $a_2 = -0.343$, $a_3 = -0.135$, $a_4 = -0.137$, $a_5 = 0.150$, $a_6 = -0.047$, $a_7 = 0.007$, $a_8 = -0.059$, $a_9 = -0.033$, $a_{10} = -0.022$, $a_{11} = -0.02$, $a_{12} = 0.0$, $a_{13} = -0.04$, $a_{14} = 0.215$, $a_{15} = -0.175$, $a_{16} = -0.218$, $a_{17} = 0.053$, $a_{18} = 0.006$, $a_{19} = 0.0$, $a_{20} = -0.003$, $a_{21} = -0.003$, $a_{22} = 0.040$, $a_{23} = 0.027$, $a_{24} = 0.0$, $a_{25} = -0.029$, $a_{26} = 0.011$, $a_{27} = 0.120$.

We have set each equation(k = 1, 13) to zero:

$b_6(a_2 + a_{13}.F_1 + 2a_8.F_2 + a_{18}.F_3 + a_{20}.F_5 + a_{21}.F_6) = 0$
$b_3(a_1 + 2a_7.F_1 + a_{13}.F_2 + a_{14}.F_3 + a_{15}.F_4 + a_{16}.F_5 + a_{17}.F_6) = 0$
$b_8(a_3 + a_{14}.F_1 + a_{18}.F_2 + 2a_9.F_3 + a_{22}.F_4 + a_{23}.F_5) = 0$
$b_{15}(a_6 + a_{17}.F_1 + a_{21}.F_2 + a_{26}.F_4 + a_{27}.F_5) = 0$
$b_{11}(a_4 + a_{15}.F_1 + a_{22}.F_3 + 2a_{10}.F_4 + a_{25}.F_5 + a_{26}.F_6) = 0$
$b_{13}(a_5 + a_{16}.F_1 + a_{20}.F_2 + a_{23}.F_3 + a_{25}.F_4 + 2a_{11}.F_5 + a_{27}.F_6) = 0$

The above equations can be solved for the F's and, subsequently, for the values x_i by using, for example, the mathematical programming package Maple. Checking whether Q is maximum is a little more complicated but several techniques are available in the literature on numerical optimization.

6. Related Work

Most existing research in DAI adopts a solution-oriented approach, as opposed to a theory-oriented approach, and is directed at demonstrating the validity of constructs and approaches for modeling specific phenomena or solving specific classes of problems. However, there are several exceptions as follows.

Lesser and Decker [6,8,13,14] conducted research directed at the design of coordination mechanisms using their effectiveness on the characteristics of the tasks and the environments. Huberman and associates [7,9,10,11] have worked on statistical physics-based models of Intelligent Agent Systems in relation to resource contention and predictive behavior. Gasser gives a detailed account of the range of DAI approaches to coordination[12]. Findler and associates examined variations in system behavior in terms of variations of the precision of agents' models [15,15,17,18]. We also single out the excellent book by Cohen on empirical methods in Artificial Intelligence [19].

7. Conclusions

We can state that coordination is a combination of a variety of mechanisms aimed at substituting for the unattainable perfect world of complete and uptodate knowledge of goals, plans, actions and interactions as well as of agents' unlimited processing and communication power. This is done by means of an appropriate and adaptive organizational structure (well-balances division of labor and flexible interaction among agents), exchanging meta- level information (e.g., control information, planning methods, credible commitments, joint model building of the environment), and reducing logical coupling and resource dependencies of agents (effective techniques for task allocation, resolving resource conflicts and logical contradictions, and the like).

In this exploratory work, we have outlined and proven the feasibility of an approach that can lead to quasi-optimum coordination in a characteristic subset of MAS. Because of the limited number of control variables (CVs) incorporated in the system at this stage, this paper does not present the quantitative aspects of their role in the management of coordination.

References

[1] T. W. Malone & K. Crowston, "*The interdisciplinary study of coordination*," ACM Computing Surveys, 26(1):87-119, 1994.

[2] N .V. Findler, "*Distributed knowledge-based systems in manufacturing*," In G. Pzevski, ed., Artificial Intelligence in Manufacturing, 17-33, Springer Verlag, 1989.

[3] N. V. Findler & J. Gao, "*Dynamic hierarchical control for distributed problem solving*," Data and Knowledge Eng., 2:285-301, 1987.

[4] N. V. Findler & Q. Ge, "*Perceiving and planning before acting - an approach to enhance global network coherence*," International Conf. of Intelligent Systems. 4:459-470, 1989.

[5] R. Axelrod, *The Evolution of Cooperation*, Basic Book, NY, 1984.

[6] K. S. Decker, E. H. Durfee, & V. R. Lesser, "*Evaluating research in cooperative distributed problem solving*," In L. Gasser & M. N. Huhns, eds., Distributed Artificial Intelligence, Vol. 2, CH. 19, 485-519, Morgan Kaufmann, 1989.

[7] B. A. Huberman & N. Glance, "*Diversity and collective action*," In H. Haken & A. Mikhailov, eds., Interdisciplinary Approaches to Nonlinear Systems, Springer, 1993.

[8] K. S. Decker, *Environment-Centered Analysis and Design of Coordination Mechanisms*, PhD dissertation, Univ. of Massachusetts at Amherst, May 1995.

[9] T. Hogg & B. A. Huberman, "*Controlling chaos in distributed systems*," IEEE Trans. on Systems, Man and Cybernetics, 21(6):1325-1332, 1991.

[10] B. A. Huberman & N. Glance, "*Evolutionary games and computer simulation*," Proc. of the Nat. Ac. of Sciences, 90(16):7715-7718, 1993.

[11] B. A. Huberman & T. Hogg, "*The behavior of computational ecologies*," In B. A. Huberman eds., The Ecology of Computation, 117-132, Elsevier Science B, 1988.

[12] L. Gasser, *DAI approaches to coordination*, In N. M. Avouris & L. Gasser, eds., Distributed Artificial Intelligence: Theory and Praxis, 31-51, Kluwer, 1992.

[13] K. S. Decker & V. R. Lesser, "*Quantitative modeling of complex computational task environments*," In Proc. of the 11-th Nat. Conf. on Artificial Intelligence, 217-224, 1993.

[14] K. S. Decker, "*Task Environment centered simulation*," In M. Prietula, K. Carley & L. Gasser, eds., Simulating Organizations: Computational Models of Institutions and Groups, 1996.

[15] N. V. Findler & R. M. Malyankar, "*An empirical approach to a hheory of coordination. Part I: Design principles and First Results*," Computational & Mathematical Organization Theory, 6(2):119-144, 2000.

[16] N. V. Findler & R. M. Malyankar, "*Social structures and the problem of coordination in intelligent agent societies*," IMACS World Congress 2000, 122-134, 2000.

[17] R. M. Malyankar, N. V. Findler & P. S. Heck, "*The effects of satisficing models on coordination*," AAAI Spring Symposium, TR SS-98-05, 39-45, AAAI Press, 1998.

[18] R. M. Malyankar & N. V. Findler, "*A methodology for modeling coordination in intelligent agent societies*," *Computational and Mathematical Organization Theory*, 1, 317-345, 1998.

[19] P. R. Cohen, *Empirical Methods for Artificial Intelligence*, The MIT Press, 1995.

Eun Gyung Kim

She received the B.S. degree in Physics from Sook-Myung Women's University in 1984, and the M.S. degree in Computer Science from Chung-Ang University in 1987. In 1991, she received the Ph.D. degree in Computer Engineering from Chung-Ang University. She is currently a professor at the School of Information Technology, Korea University of Technology and Education (KUT), Choenan, Korea. Her research interests include Distributed Artificial Intelligence, Multi-Agent System, and Rule-Based Management System. She was a visiting researcher in the Department of Computer Science and Engineering of Arizona State University during the years 2001-2002.

Phone : +82-41-560-1350
E-mail : egkim@kut.ac.kr