Advances in Natural Computation – Vol. 5

ADAPTATION AND EVOLUTION IN COLLECTIVE SYSTEMS

Akira Namatame

ADAPTATION AND EVOLUTION IN COLLECTIVE SYSTEMS

ADVANCES IN NATURAL COMPUTATION

Series Editor: **Xin Yao** (University of Birmingham, UK)

Assoc. Editors: **Hans-Paul Schwefel** (University of Dortmund, Germany)
Byoung-Tak Zhang (Seoul National University, South Korea)
Martyn Amos (University of Liverpool, UK)

Published

Vol. 1: Applications of Multi-Objective Evolutionary Algorithms
Eds: Carlos A. Coello Coello (CINVESTAV-IPN, Mexico) and
Gary B. Lamont (Air Force Institute of Technology, USA)

Vol. 2: Recent Advances in Simulated Evolution and Learning
Eds: Kay Chen Tan (National University of Singapore, Singapore),
Meng Hiot Lim (Nanyang Technological University, Singapore),
Xin Yao (University of Birmingham, UK) and
Lipo Wang (Nanyang Technological University, Singapore)

Vol. 3: Recent Advances in Artificial Life
Eds: H. A. Abbass (University of New South Wales, Australia),
T. Bossomaier (Charles Sturt University, Australia) and
J. Wiles (The University of Queensland, Australia)

ADAPTATION AND EVOLUTION IN COLLECTIVE SYSTEMS

Advances in Natural Computation – Vol. 5

Akira Namatame
National Defense Academy, Japan

World Scientific

NEW JERSEY • LONDON • SINGAPORE • BEIJING • SHANGHAI • HONG KONG • TAIPEI • CHENNAI

Published by

World Scientific Publishing Co. Pte. Ltd.
5 Toh Tuck Link, Singapore 596224
USA office: 27 Warren Street, Suite 401-402, Hackensack, NJ 07601
UK office: 57 Shelton Street, Covent Garden, London WC2H 9HE

British Library Cataloguing-in-Publication Data
A catalogue record for this book is available from the British Library.

ADAPTATION AND EVOLUTION IN COLLECTIVE SYSTEMS
Advances in Natural Computation — Vol. 5

ISBN 981-256-856-6

Printed in Singapore by World Scientific Printers (S) Pte Ltd

This book is dedicated to those
who have made my academic-life exciting.

This page is intentionally left blank

Preface

It is thought that ants in an ant colony do not know exactly how the ant colony where they live should be built. Each ant has certain things that it does in coordinated association with other ants, but no ant designs the colony. How the colony of ants works collectively in the manner it does remains a mystery. However, an important clue to the answer to this question may be found by looking at interactions among ants.

Many organisms form collectives that strongly affect the behavior of individuals. Familiar examples include the schooling behavior of fish and the flocking behavior of birds. Collective behavior emerges from traits of individuals. Collectives emerge from relatively simple traits of individuals, and these traits give rise to individual behaviors that form the collective. Collectives can be treated as an additional level of organization between the individual and the population.

For the last decade, attempts have been made to develop some general understanding, and ultimately a theory of systems that consist of interacting agents. It is common to call these systems *collective systems* because it is difficult to reduce aggregate behavior to a set of properties characterizing the individual components. Interactions produce properties at the aggregate level that are simply not present when the components are considered individually.

In his book, titled *The Wisdom of Crowds*, Surowiecki (2004) explores an idea that has profound implications. A large collection of people are smarter than an elite few, no matter how brilliant they are and or how much better they are at solving problems, fostering innovation, coming to wise decisions, even predicting the future. His counterintuitive notion, rather than crowd psychology as traditionally understood, suggests new insights regarding how complex social and economic activities are organized. He explains the *wisdom* of crowds emerges only under the right conditions, which are (1) diversity, (2) independence, (3) decentralization, and (4) aggregation.

On the other hand, the fact that selfish behavior may not achieve full efficiency has been well reported in the literature. Recent research efforts have focused on quantifying the loss of system performance due to selfish and uncoordinated behavior. The degree of efficiency loss is known as the *price of anarchy*. We need to design systems so that selfish individual behaviors need not degrade the system performance.

In this book, a collective system, or simply a *collective*, is modeled as a collection of autonomous decision-making entities, called *agents*. A collective refers to any complex system of interacting agents, together with performance measures by which we can rank the behavior of the entire system. Collective systems include a collection of diverse and mutually adaptive agents pursuing varied and often conflicting interests. The collective systems are situated between a few agents in game theoretic systems, a few hundred agents in multi-agents systems, and a larger scale of agents in typical economic and social systems.

The mission of collective evolution is to harness the collective systems of selfish agents and to serve to secure a sustainable relationship in an attainable manner so that desirable properties can emerge as *collective intelligence*. Of particular interest is the question as to how social interactions can be restructured so that agents are free to choose their own actions while avoiding outcomes that none would have chosen.

Darwinian dynamics based on mutation and selection form the core of models for evolution in nature. Evolution through natural selection is understood to imply improvement and progress. If multiple populations of species adapt to each other, the result is a co-evolutionary process. The problem to contend with in co-evolution based on the Darwinian paradigm, however, is the possibility of an escalating arms race with no end. Competing species might continually adapt to each other in more and more specialized ways, never stabilizing at a desirable outcome.

In biology, the gene is a better unit of selection by which to represent individuals. However, the collective evolutionary process is expected to compel agents towards ever more refined adaptation and evolution, resulting in sophisticated behavioral rules. The persistence and sustainability of the collective system in turn depends on its persistent collective evolution.

Hardware developments will soon make possible the construction of very-large-scale models, for instance, models that contain one million to 100 million agents. It has been argued that the main impediment to creating empirically relevant agents on this scale is our current lack of understanding of the realistic behavior of agents. This bottleneck, i.e., what rules to write for agents, is the primary challenge facing the agent research community. The approach of collective evolution is very much at the forefront of this issue.

As is usual in the case of any book, the author is deeply indebted to several people. My friends and colleagues, the authors of the books and papers to which I have referred herein, have contributed to this book in many ways. I would like to thank those colleagues who provided stimulating academic interactions through debate and dialog through readings, including Professors Yuji Aruka, Robert Axtell, David Green, Dirk Helbing, Taisei Kaizoji, Thomas Lux, Robert MacKay, Hidenori Murakami, Frank Schweitzer, Bernard Walliser, and Xin Yao. I would also like to Associate Professors Hiroshi Sato and Masao Kubo, my many wonderful students at the National Defense Academy, Japan, who provided a quiet retreat from the pressures of teaching and administration during the editing of this book.

Above all, there is my family. My wife Kazuko and our daughters Aya and Kaori have all supported me and tolerated my bringing my work home with me. I would also like to thank Mr. and Mrs. Russell and Lynn Phillips who taught me how to write a thesis when I was a student at Stanford University 30 years ago. Since my college years, they have observed my progress, but I have struggled with speaking and writing in my second language. Finally, I would like to thank all of you who will take the time to read this book. I hope that you will learn as much from reading this book and as I have learned through its writing.

Akira Namatame

This page is intentionally left blank

Contents

This page is intentionally left blank

Chapter 1

Introduction to Collective Systems

A collective system is a large system of adaptive agents, where each agent has her own utility function to optimize, along with global performance measures of the full system. The envisioned objective is to study the mechanism of inducing desirable collective outcomes. This aim is quite novel, since a collective of agents needs to establish coordinated and synchronized behavior from the bottom up. In this chapter, we provide a survey of approaches to the study of collective systems.

1.1 Collective Outcomes of Interacting Agents

Billions of people make billions of decisions everyday about many things. It often appears that the aggregation of these unmanaged individual decisions leads to a desired outcome. It is amazing that economic and social activities generally work well in this way without any authority. Adam Smith characterized this fact by stating that an "*unseen hand*" brought about coordination among self-interested individual economic activities. The unseen hand is observed behind many market activities. This principle also works as a basic mechanism for allocating limited resources to people who need them.

People constantly interact with each other in different ways and for different purposes. Somehow these individual interactions produce some coherence at the aggregate level, and therefore, aggregation may generate structure and regularity. The individuals involved may have a very limited view of some part of the whole system but their activities are coordinated to a large degree and produce a desirable outcome at the aggregate level.

However, there are other systems for which it is difficult to understand how they work or to find out better ways to make them work. For instance, many economic and social systems often produce inefficient outcomes at the aggregate level in a way that the individuals who comprise the system need not know anything about or even be aware of it. When the system results in some undesirable outcome, we often think about whether it is due to the members who comprise the system. We tend to observe the resulting outcome as corresponding to the intentions of the members who compromise the system.

There is strong interest in many fields to answer the following questions. How do interacting individuals with micro-motives produce the aggregate outcome? How do we identify the micro-rules of agents that produce some regularities of interest at the macroscopic level? There has been no natural methodology for systematically studying these issues.

Most of our social activities are substantially free of centralized management, and although we may care how it all comes out in the aggregate, our own decisions and behaviors are typically motivated by self-interest. Therefore, in examining collective behavior, we shall draw heavily on the individual decisions. It might be argued that understanding how individuals make decisions is sufficient to understand most parts of the collective system. Although individual decisions are important to understand, they are not sufficient to describe how a collection of agents arrives at specific decisions. These situations, in which the decision of an agent depends on the decisions of others, are situations that usually do not permit any simple summation or extrapolation to the aggregate (Schelling,1978). To make this connection, we usually have to look at the system of interactions among agents.

We usually ascribe human behaviors as if they are oriented toward a goal. Peoples have preferences and pursue their own goals, or maximize comfort as well as minimize effort embarrassment. We might characterize these behaviors as *purposive behaviors*. Economists argue that much of individual private consumption is also dependent upon other peoples' consumption. We often behave by reacting to others. Therefore, what we also have is a mode of *contingent behavior* that depends on what other people are doing (Schelling, 1978). For example, each person's enjoyment of driving a car is inversely related to others' enjoyment if too many peoples drive. Everybody becomes stuck in congested traffic in this case. This is a kind of social congestion and the problem is that there is no way of knowing what others will do. When we are in a mode of contingent behavior, the resulting collective behavior is often volatile and far from desirable.

It is not easy to tell from collective phenomena just what the motives are behind individuals and how strong they are. For instance, consider a traffic jam again. It is not easy to capture the properties of a traffic jam at the aggregate level without describing what individual drivers do. Each of these drivers is different, and the characteristics of their driving behavior become the rules in the model. When we run this model we can reproduce a traffic jam, but this time we need to watch closely how the individual drivers interact with each other and we can inject to see how these interactive behaviors among drivers would affect the visible properties of the traffic jam (Resnick, 1999)(Bonabeau, 2002).

Therefore, we have to look closely at agents who are adapting to other agents. In this way, the behavior of one agent affects the behaviors of the other agents. How well agents accomplish what they want to accomplish depends on what other agents are doing. What makes this kind of interactive situation interesting and difficult is that the aggregate outcome is what has to be evaluated, not merely how agents behave within the constraints of their own environments.

How well they do for themselves in adapting to environments is not equivalent to how satisfactory a social environment they collectively create for themselves. There is no presumption that the self-serving behavior of agents should lead to collectively satisfactory results. If our problem is that there is too much traffic, we are also part of the problem. If we raise our voice to make ourselves heard, we add to the noise level that other people are raising their voices to be heard over.

Our complex systems often result in the features of *emergent properties*, which are properties of the system that separate components do not have. These emergent properties, we find, are the result of not only the behavior of individual agents but the interactions between them as well. For instance, what drivers do on the road depends on what other drivers do. This can not be explained without looking at how the agents behave and interact with each other to make up the whole. Resulting traffic jams are counterintuitive phenomenon that we could only predict with the framework of the collective system of interacting agents.

We can observe many collective phenomena viewed as *emergence* that has arisen from billions of small-scale and short-term decisions of interacting agents. Viewing complex systems as a collective of interacting agents means adopting a new scientific approach that shifts from *reductionism* to *connectionism.*

With the view of reductionism, every phenomenon we observe can be reduced to a collection of components, the movement of which is governed by the deterministic laws of nature. In such reductionism, there seems to be no place for novelty or emergence. The basic approach with the view of reductionism is the rational choice model. The rational choice theory posits that an agent behaves to optimize her own utility produces relevant and plausible prediction about many aggregate phenomena.

However, there are many critics of approaches based on the *rational choice model.* The problem of the rational choice model is that it assumes agents who are sufficiently rational. Goals and purposes of agents are also often related directly to other agents or they are constrained by an environment that consists of other agents who are pursuing their own goals.

When a society or organization faces some complex problems, the typical reaction is to fall into "*centralized thinking*" (Watts, 2001). A small coherent group of experts decide what to do based on the characteristics of the problem, and execute rules and everyone else then simply follows these rules. However, introducing additional rules can serve only to make the problem worse. This is because it is usually centralized thinking behind these local rules, so the effect of new local rules being added to existing local rules is quite strong. Without modeling the process of the chains of reactions, it would be very hard for a human brain to predict this pathological collective behavior.

To understand this paradox, we need to take a look at the problem of "*decentralized thinking*" (Resnick, 1999). What should be clear is that combining the many different individuals involved at a single point is almost certain not to succeed in delivering the kind of essential functionality. Some other kind of connectionism is required.

1.2 The Study of Collective Systems

A collective system is modeled as a collection of autonomous decision-making entities, called agents. In this section, we provide the definition and a survey of approaches to collective systems. A collective system, or just simply a collective, means any complex system of interacting agents, together with performance measures by which we can rank the behavior of the entire system (Tumer and Wolpert, 2004). Collective systems include a collection of diverse and mutually adaptive agents pursuing varied and often conflicting self-interests.

Many organisms form aggregations that have strong effects on individual behaviors. Familiar examples include schools of fish and flocks of birds. Auyang (1998) defines the term "*collective*" for such aggregations. According to Auyang, the defining characteristics of a collective are as follows. Interactions among individuals making up a collective are strong, that is internal cohesion is strong while external interactions are weak. Furthermore, collectives have their own characteristics and processes that can be understood independent of the individuals that compromise them.

Another defining characteristic of collectives in ecological systems is that collectives exist for longer or shorter times than do the individuals making up the collective. Collectives can be treated as an additional level of organization between the individual and the population (Grim, 2005). Individuals belonging to a collective may behave very differently from individuals alone, so different traits may be needed to model in individuals that are not in a collective.

The behavior of a collective emerges from traits of individuals. A school of fish is an example of modeling a collective as emerging from relatively simple traits of individuals, and these traits give rise to individual behaviors that form the collective. Representing a collective explicitly does not mean that individuals are ignored. Instead, a collective can also be represented by the manner in which individual