CIMCA 2001 Proceedings/ISBN 0858898470: M. Mohammadian (Ed.)

Collective decision making using natural self-organization in distributed systems

O. Kornienko, S. Kornienko and P. Levi
Institute of Parallel and Distributed High-Performance Systems,
University of Stuttgart, Breitwiesenstr. 20-22, D-70565 Stuttgart, Germany.
E-mail: {kornieoa, korniesi, levi}@informatik.uni-stuttgart.de

Abstract

Distributed systems without centralized elements need a distributed mechanism that allows accomplishing the control and synchronization tasks. This problem is especially relevant in nano- and biosystems that do not possess complex computational devices. However the collective coordination and decision making may be performed using the available in these systems natural dynamical processes based on chemical, optical, electromagnetic or quantum effects. Utilizing these dynamical processes, the transfered information within distributed system is firstly efficiently coded, secondly, does not contain the global information about the whole system. This guarantees security and privacy being also very important in other fields, e.g. in e-commerce.

1 Introduction

Distributed systems without centralized coordination are employed in many branches of computer science and lately often in bio- and nanotechnology (e.g. [1], [2]). Specific problems encountered here consist in replacing the functions performed by central element such as synchronization [3], decision making [4], coalition formation [5] and so on. Moreover bio- and nanosystems often do not have or possess only the limited computational resources and memory capacity that restrict the information interactions among subsystems both in amount of transfered information and in the participants that this information can be directed to [6]. Similar restrictions to the information interactions but from completely other ground arise e.g. in internet, where the interactions need to be restricted by the reason of security and privacy. Often the number of participants in such distributed systems is also unknown. Decision making in these systems has also a specific form. Direct usage of conventional procedures of the knowledge(rule)-based processing (e.g. [4]) is here restricted by two reasons: firstly, these procedures need collective information describing the whole system, secondly, due to limitation of computational resources this collective information as well as the processing rules have to be efficiently coded and compressed.

Considering bio- and nanosystems, one can remark they possess natural dynamic processes determined by chemical, optic, electromagnetic or quantum effects (e.g. [6]-[8]). These dynamical processes from the mathematical viewpoint are suitable to be underlying the synchronization and decision making in such distributed systems. In this case interactions among subsystems may be performed e.g. by an electromagnetic field or by a concentration of chemical agents. Using available nonlinear elements, the information processing can be also distributed among participants, therefore centralized computational devices are not needed. Collective information processing based on the dynamical processes has another advantage over traditional approaches. From the synergetics [9] it is known that any distributed system demonstrating collective behaviour (e.g. decision pattern, synchronized behaviour and structure) possesses some dynamical values often denoted as order parameters (OPs). They have dual nature: on the one hand they describe the collective activity of the whole system, i.e. self-organization, on the other hand they are distributed among participants. In this way the OPs allow designing the desired collective behaviour of distributed system without using any centralized elements.

The order parameters describe the qualitative changes of collective behaviour given in the case of decision making by the macroscopic decision pattern. Before the distributed system comes to mutual agreement the decision pattern has chaotic or more commonly not ordered structure. After achieving the needed agreement, the decision pattern is being ordered. Generally speaking the derived OPs show whether the distributed system is able to achieve the collective decision. Therefore it is natural to assume the desired collective process may be predetermined by the corresponding OPs. Forasmuch as the order parameters depend on subsystems and interactions (couplings) among them, the needed modifications, given by the predetermined OPs, can be obtained in the distributed system by changing interactions (couplings) or subsystems. In other words the systematic approach towards modifying or creating the desired self-organization process among components of distributed system has been suggested that thereby guarantees the needed collective information processing.

The natural dynamical systems mentioned above are described by the corresponding mathematical models. Therefore the first problem consists in obtaining the OPs and adjusting their form so that to make them suitable for decision making. This form of order parameters imposes the defined conditions on the couplings among the subsystems. Performing the successive propagation of these conditions and taking into account the given natural restrictions, we get the couplings that guarantee achieving the desired common agreement. The second problem is to make this approach compatible for usage in conventional computer systems, where we suggest a hybrid structure of the subsystem-participant containing analytic as well as algorithmic structures. Finally, the whole approach is demonstrated on the computer simulation of moving agents that can be considered as a prototype of robotic or nanorobotic system.

2 General principles

Analytical approach towards investigations of distributed systems encounters some typical problems caused mainly by high complexity degree of these systems. Therefore analyzing the distributed systems, it is necessary to reduce their complexity. Basis of such a reduction is given by the following observation. Forasmuch as there are no centralized elements the control over the whole system is performed in the distributed way by means of specific interactions among subsystems being autonomous. From this viewpoint the complexity of separate subsystem determines the ability of action, perception, processing, etc. Distributed control is determined primarily by the ability of interaction and by distributed structure of the whole system. It means, investigating distributed control, one can build the sequence of simplified models (see Figure 1), if they will preserve a similar structure, i.e. they will have independent components that are able to perform specific interactions.

In this way one can distinguish three simplification levels.

The first (algorithmic) simplification level is represented by multi-agent systems (MAS), where an agent on this level is in fact the simplified model of a Real World (RW)-subsystem. Negotiations among subsystems-participants on this level is a dynamical process whose result is represented by common agreement about some statement. The kind of this statement may be different, e.g. decision about the next step of a plan, coordination, monetary value and so on. Observing the decision making systems, one can distinguish the structure supporting this dynamical process of negotiation and the further structures implementing the made decision. The structural scheme of a system having decision and supporting modules, denoted further as analytical and algorithmic agents, is shown in Figure 2.

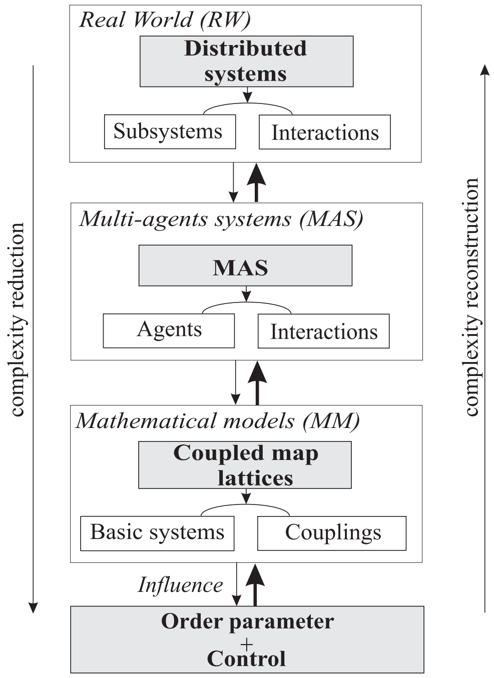


Figure 1: Systematic approach to the analysis and control of collective phenomena in distributed systems using the synergetic methodology.

The principles underlying the decision module are unique, whereas the supporting module depends on implementation details, environment and so on. It is especially obvious on the example with the moving robots which are completely different in the hardware realization however use similar algorithms of decision making (e.g. [2], [12]). Therefore being motivated by above mentioned reasons, we suggest to discouple both modules and to focus further on the analytic agent whereas algorithmic one will be leaved for the specific realization on the RW and MAS levels.

The second (mathematical) simplification level is given by such a mathematical object as the coupled map lattices (CML) [11]. In this case the basic maps on the Mathematical Models (MM)-level present the simplified (idealized) model of an analytical agent. Accordingly, the interaction among analytical agents corresponds to the coupling among maps.

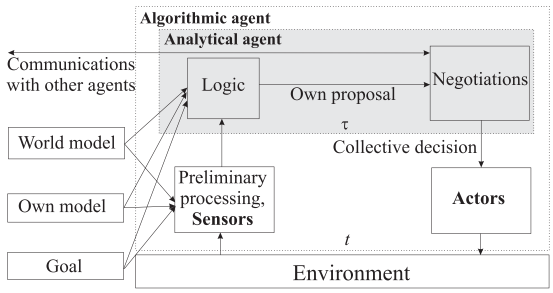


Figure 2: Autonomy cycle of a subsystem-participant consisting of analytical and algorithmic parts.

From the viewpoint of synergetics the collective behaviour of coupled maps is a result of selforganisation between internal components of initial maps. Such internal components are often denoted as modes. It turned out that only a few modes stand in a generation of collective behaviour. Therefore in case the dimension and degrees of freedom of coupled system can be reduced to these modes one can get the compact analytical characterization of the collective phenomena, so-called order parameter (OP) [9]. Systematicalness of this procedure guarantees reconstruction of the complexity at the backward transformation from OP to the initial system.

The dynamics of CML-model can be viewed as a process of negotiations and thereby the initial map itself determines the local negotiation strategy for every agent. In this case the order parameter demonstrates whether the overall system is able to achieve a mutual agreement in a finite time. Correspondingly the behaviour of the order parameter equation can be modified so that to guarantee a desired collective decision with the chosen evaluation criterion. Then returning back to MM and MAS levels, one can determine changes of the couplings (interactions) among maps (agents), caused by a modification of the order parameter.

3 Analytical agent

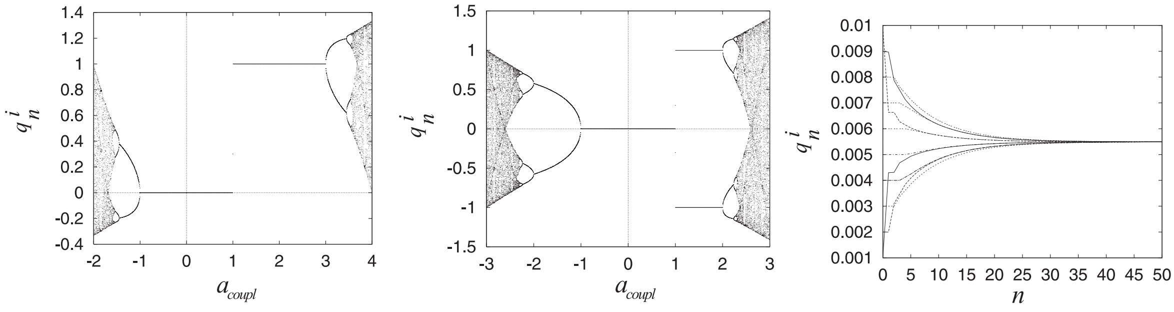
Analytical agent shown in Figure 2 represents the module that on the base of communications with other such modules deliver the common decision for further processing by the algorithmic part. The main idea is that the analytic agent may be implemented by dynamical systems being available in the given environment. Forasmuch as the desired negotiation processes is primarily determined by interactions (couplings) therefore a wide range of these basic dynamical systems is allowed. There is one requirement imposed on the dynamical systems that the results of dynamical process i.e. decisions should be robustly recognized by the algorithmic agent.

Choosing an example exemplifying the mentioned approach, we are motivated by robotics. The dynamical systems used here possess mainly discrete nature of time, therefore we focus further on this type of dynamical systems. In the first case it is assumed there is a lot of fixed decisions and every agent votes for one of them. Individual agent is motivated by own reasons however the whole group during negotiation session should achieve the common agreement. The most simple discrete dynamical systems suitable for this kind of dynamics are given by the perturbed normal forms of transcritical and pitchfork bifurcations [13]

$$q^i_{n+1} = a_{coupl} \cdot (q^i_n - (q^i_n)^2) + (q^i_n)^2, \quad i = 1, ..., m, \tag{1}$$
$$q^i_{n+1} = a_{coupl} \cdot (q^i_n - (q^i_n)^3) + (q^i_n)^3, \quad i = 1, ..., m, \tag{2}$$

whose bifurcation diagrams are shown in Figure 3(a) and (b). The bifurcation parameter a_{coupl} is in fact the coupling function $a_{coupl}(q^1_n, q^1_n, ..., q^m_n)$ where m is the dimension of the coupled system. For the system (1) the value of a_{coupl} in the region [-1,1) leads to the stationary state $q_{st_1} = 0$ and in the region (1,3] to the $q_{st_2} = 1$. These values can be viewed as a logical "0" and logical "1" for the further processing in the algorithmic agent. The system (2) possesses three stationary states "-1", "0", and "1" that are correspondingly suitable for coding three possible decisions. In case more potential decisions are needed it is reasonable to use the approaches that sequentially browse all possible decisions.

As already mentioned above, the common agreement achieved by a distributed system can be presented not only by fixed values but also can be given by some value in the defined range (e.g. result of auction). It is only assumed that the calculation algorithm



(a) (b) (c)

Figure 3: The bifurcation diagrams ($m = 1$): **(a)** of the system (1); **(b)** of the system (2) (with positive and negative initial conditions); **(c)** The behaviour of state variables q_n^i of (3) using (4) and remarks in Sec. 5 ($m = 10$) with the initial values $q_0^{1,2,...,10} = \{0.1, 0.2, 0.3, ..., 0.9, 0.99\}$. The calculated arithmetical mean value is equal to 0.549.

of this value is formalized by logical or arithmetical formula. In the simple case we are trying to calculate the arithmetical mean value from initial proposals of participant agents. The number of these agents is unknown and moreover every agent obtains information only about communicated neighbours (global information is not allowed). In this case we suggest using the following simple dynamical system

$$q_{n+1}^i = f_{cont} \cdot (q_n^i + a_{coupl}), \quad i = 1, ..., m, \tag{3}$$

where f_{cont} is the control function determining the required result.

4 Couplings among analytical agents

Analytical agents, performing negotiation, are interacted together. However from the mathematical viewpoint agents are represented by the corresponding dynamical systems that are coupled together. In this context the coupling implies not only the way of connections, but also the way of communication, i.e. it is a mathematical analogue of interaction. Changing the coupling among basic dynamical systems, we can correspondingly exert an influence on the output results of negotiation procedure. Determining the result of negotiation, we do not mean hereby to fix the decision, we only guarantee that the system is able to achieve the final decision in finite time. Therefore the type of initial system is not so important because the result may be changed by the accordingly adjusted couplings. The coupling can be performed either locally i.e. among neighbour agents or globally i.e. in the group. Generally the choice of the neighbours for coupling may have the random nature. We assume only that during one communication session the agents build some kind of closed chain, whereas during the next session the agents may be ordered in another way.

Considering the moving robots with chemical [2] or optical [12] communication channels that have mainly local interaction nature, we assume every agent can perform communication with two local neighbours, i.e. $a_{coupl}(q_n^{i+1}, q_n^{i-1})$. Thus the interacting agents represent a two-way coupled ring (taking into account the boundary conditions for q_n^{i+1}, q_n^{i-1}). The coupling function $a_{coupl}(q_n^{i+1}, q_n^{i-1})$ is selected as the following polynomial

$$a_{coupl}(q_n^{i+1}, q_n^{i-1}) = k_0 + k_1 q_n^{i+1} + k_2 q_n^{i-1} + O((q_n^{i+1})^2, (q_n^{i-1})^2), \quad (4)$$

where k_j are coefficients. Solution of this problem is expected to be given by coefficients k_j of coupling function (4). In case the solution can not be found the order of (4) will be increased until the solution will be obtained.

5 The order parameters

As mentioned above the collective agreement represents a qualitative change in the group behaviour described by macroscopic order parameters. As can be observed from Figure 1 there are bottom-up and top-down approaches to derive the order parameters. Utilizing bottom-up approach the basic systems of the CML model are being consecutively reduced until the OP will be obtained. However, forasmuch as the coupling polynomial (4) is not yet determined on this step, the OP derivation procedure can not be applied to the CML model. Therefore our suggestion consists in using the top-down approach, where first an assumption about dynamics of order parameters is made, then all needed modifications are propagated into the CML model.

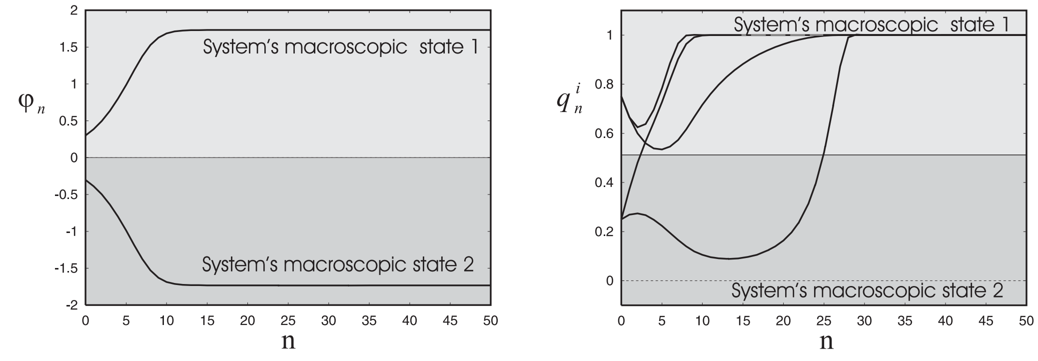
Considering macroscopic dynamics of simple voting systems introduced in Sec. 3, one can remark the negotiation will be ended up when all participants achieve mutual agreement, i.e. all will vote for only one of initial proposals. This kind of macroscopic dynamics is very similar to the case of coexisting attractors (e.g. [9]) illustrated by the following one-dimensional normal form

$$\varphi_{n+1} = \lambda_u \varphi_n + \mu_3 \varphi_n^3 + O(\varphi_n^4), \quad (5)$$

where $\lambda_u > 1$ and $\mu_3 < 0$ are coefficients. The system (5) possesses three stationary states $\varphi_{st_{1,2,3}} = \{0, \sqrt{\mu_3(1-\lambda)}/\mu_3, -\sqrt{\mu_3(1-\lambda)}/\mu_3\}$ and for $\lambda_u > 1$ the state φ_{st_1} is unstable and $\varphi_{st_{2,3}}$ are stable. As shown on Figure 4(a) the attractor that the state variable φ_n will be attracted to is determined by initial conditions, namely $\varphi_0 > 0$ for φ_{st_2} and $\varphi_0 < 0$ for φ_{st_3}. In other words the long time dynamics of the system with the coexisting attractors is determined by the initial conditions, i.e. by their so-called attraction basins (e.g. [13]).

Using the synergetic slaving principle [9], this kind of dynamics can be expanded to the initial system (1). In this case m state variables, starting from one of these basins, will be attracted to the appropriate attractor. However if the state variables start from different basins they will compete for the attractor that these variables will be attracted to (see Figure 4(b)). The negotiation (here a voting procedure) can be based on this competition where the initial conditions of coupled systems (1) play a role of agents's initial proposals, e.g. "0.25" for "macroscopic state 0" and "0.75" for "macroscopic state 1".

If the distributed system has taken the collective agreement it means that all state variables q_n^i of coupled systems (1) get the same values. Now let us determine the vector of stationary states of the coupled systems (1) with dimension m as $\underline{\mathbf{q}}_{st=0} = \{q_{st}^1 = 0, ..., q_{st}^m = 0\}$ and $\underline{\mathbf{q}}_{st=1} = \{q_{st}^1 = 1, ..., q_{st}^m = 1\}$. Following macroscopic assumption given by (5), we have



(a) (b)

Figure 4: **(a)** Dynamics of the system (5), where $\lambda_u = 1.3$ and $\mu_3 = -0.1$, (two times: at initial condition $x_0 = -0.3$ and at initial condition $x_0 = 0.3$); **(b)** two different initial conditions in competition dynamics of the system (1) based on the NF (5), $m = 4$.

to stabilize $\underline{\mathbf{q}}_{st=0}$ and $\underline{\mathbf{q}}_{st=1}$ whereas all other stationary states should remain unstable. Performing the linear stability analysis, we are mainly interested in the following eigenvalues $\lambda_{1,...,m}^{\mathbf{q}_{st=0}} = k_0$, $\lambda_{1,...,m}^{\mathbf{q}_{st=1}} = -k_0 - k_1 - k_2 + 2$, where subindex denotes the number of the eigenvalue, superindex shows the stationary state that the eigenvalue is evaluated on. In accordance with the macroscopic assumptions given by (5) we require

$$|\lambda_{1,...,m}^{\mathbf{q}_{st=0}}| < 1, \quad |\lambda_{1,...,m}^{\mathbf{q}_{st=1}}| < 1, \quad |\lambda_{1,...,m}^{\mathbf{q}_{st\neq0,1}}| > 1. \tag{6}$$

In addition the boundary conditions for initial map (1) are

$$k_0 + k_1(q_n^{i+1})^{max} + k_2(q_n^{i-1})^{max} < 3, \quad k_0 + k_1(q_n^{i+1})^{min} + k_2(q_n^{i-1})^{min} > -1, \tag{7}$$

where $(q_n^i)^{max}$, $(q_n^i)^{min}$ are the maximal and correspondingly minimal values of state variables q_n^i. Conditions (6) can be simplified by the following assumption:

- *We suppose some of "unstable" stationary states* $\underline{\mathbf{q}}_{st\neq0,1}$ *can be also stable. The arisen thereby simultaneously stable stationary states can be absorbed by appropriate choice of initial conditions.*
- *From m eigenvalues* $|\lambda_{1,...,m}^{\mathbf{q}_{st\neq0,1}}| > 1$, *evaluated on stationary state, only one has to be unstable.*
- *Forasmuch as all initial systems (1) are identical and they are coupled in (4) by symmetrical coupling it is expected that their eigenvalues are also equal. Therefore it needs to consider instead of all* $\lambda_{1,...,m}$ *only one from them for the conditions* $|\lambda_{1,...,m}^{\mathbf{q}_{st=0,1}}| < 1$.

Moreover a solution of the inequalities (6) and (7) is simplified by the stationary states that are equal to 0 or 1. Finally we get the linear system of inequalities that can be solved by programs of symbolic manipulations like Maple or Mathematica. Performing the needed calculation, we get finally $k_0 = 0$, $k_2 = k_1$, $\frac{1}{2} < k_1 < \frac{3}{2}$. These coefficients k_j stabilize the required stationary states, moreover they fulfil the requirement $\mu_3 < 0$ in (5). The last problem consists in determining the boundary of attraction basin that specify the quota needed for taking of collective decision. For example for the quota 50% the initial conditions are 0.555544 for "0" and 0.555572 for "1", where $m = 6, ..., 10$.

Determination of the couplings coefficients for the system (3) can be performed in the same way. However we remark this system can be directly solved by using e.g. the Jordan normal form approach. Solving this system at $k_0 = 0$, $k_1 = 1$, $k_2 = 1$, we obtain the arithmetical mean value $q^i_{n\to\infty} = \frac{1}{m}\sum_{j=1}^{m} q^j_0$, setting simply $f_{cont} = 1/3$. The behaviour of the state variables q^i_n is shown in Figure 3(c).

6 Dimension scaling

The essential question arisen often in praxis concerns the dimension of the system (1). The problem is that the complexity of real applications is much higher than it can be treated analytically. In order to get round this problem we assume that some properties of the regular built CMLs are independent of their dimension. The regular or homogeneous CMLs are such coupled maps that possess equal basic systems coupled by means of the polynomials like (4). In such cases the low-dimension systems can be expanded in arbitrary high dimension without changing their linear and some nonlinear properties.

Now we would like to show that the CML (1) possesses the mentioned properties denoted further as the dimension scaling. For that we consider separately the linear and nonlinear parts of (1). Moreover it is also important to show the possible changes in the basins of initial conditions.

Linear part of (1) is given by eigenvalues of the corresponding Jacobian. Evidently that eigenvalues λ evaluated on $\underline{\mathbf{q}}_{st=0}, \underline{\mathbf{q}}_{st=1}$ (the "0" and "1" stationary states are independent of the dimension of (1)) are always equal and therefore independent of the dimension change. To show, that nonlinear part is also independent of the dimension (1), is more difficult. One possible way is to assume the eigenvalues (6) are parameters and then to derive the normal form of system (1). Considering the derived normal form, one can prove whether the nonlinear terms are independent from the dimension m. But forasmuch as all eigenvalues are equal we will get thereby the normal form of m state variables and a treatment of this topic outsteps the framework of the given work. But we can simplify the problem of nonlinear terms, if to consider only postbifurcation dynamics of system (1).

For that let $\xi^i_n = q^i_n - q^i_{st_j}$ and then substituting it into (1) and taking into account the derived coefficients k, we get the following system for the cases $q^i_{st} = 0$ and $q^i_{st} = 1$

$$\xi^i_{n+1} = \lambda^{\underline{\mathbf{q}}_{st=0}}\xi^i_n + (\xi^i_n)^2 + k_1\xi^i_n(\xi^{i-1}_n + \xi^{i+1}_n) - k_1(\xi^i_n)^2\xi^{i+1}_n, \tag{8}$$

$$\xi^i_{n+1} = \lambda^{\underline{\mathbf{q}}_{st=1}}\xi^i_n + (1-2k_1)(\xi^i_n)^2 - k_1\xi^i_n(\xi^{i-1}_n + \xi^{i+1}_n) - k_1(\xi^i_n)^2\xi^{i+1}_n, \tag{9}$$

where $i = 1, ..., m$, m is the dimension and taking into account the boundary condition for ξ^{i-1}_n, ξ^{i+1}_n. These equations are usually denoted as mode amplitude equations (e.g. [14]).

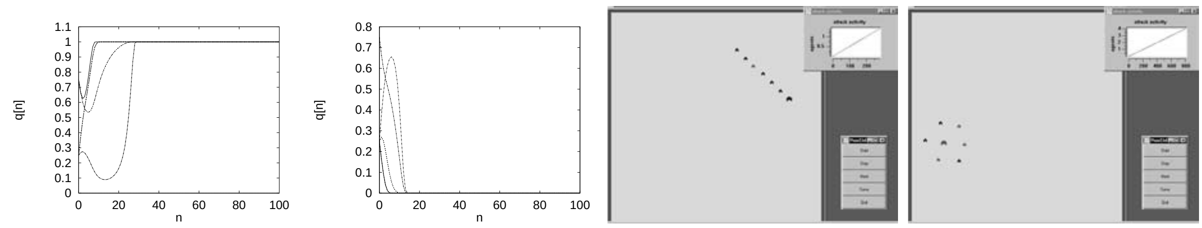
Forasmuch as $\lambda^{\underline{\mathbf{q}}_{st=0}}$, $\lambda^{\underline{\mathbf{q}}_{st=1}}$ are coefficients and $|\lambda^{\underline{\mathbf{q}}_{st=0}}| < 1$, $|\lambda^{\underline{\mathbf{q}}_{st=1}}| < 1$ we conclude that the systems (8), (9) do not undergo any local bifurcations, moreover the stationary state ξ_{st_i} is stable in the linear approximation for both systems. Therefore we can narrow down the proving and to verify that the state variables of systems (8), (9) at long time dynamics will always get zero state. The idea is that these systems because of the local couplings possess the homogeneous structure and if their state variables at dimension

$i = 3, 4, ..., j$ are really getting zero state, then in systems with $i = j+1, j+2, ..., m$ they will also get zero state.This step has been performed numerically. In this way we have in fact proved that nonlinear terms of system (1) built supercritical type of postbifurcation dynamics.

7 Simulation

As the behavioral scenario we choose the group of the moving agents, that demonstrates macroscopic spatio-temporal patterns. Each agent of this group can move in four directions on the plane, determine the distance between the neighbour agents and perceive some local external influence. This can be interpreted as e.g. "I'm attacked", however an agent is not allowed to know whether its neighbour agents are also "attacked". In case three or more agents in an arbitrary order have been simultaneously attacked, the whole group has to change the spatial formation, e.g. from the march formation to the defense formation. Thus the agents have to communicate in order to reach a mutual agreement about the spatial structure that they will behave in. Such a scenario is chosen because the sensors and the motion control of each agent is very similar to the sensors and the motion control of real robotic systems.

Each algorithmic agent sets the initial value of state variable q_0^i in analytical agent. It corresponds to the local sensor data as "0" - I'm not attacked" and "1"- I'm attacked". These logical values are coded by numerical values, following the defined specifications. The algorithmic agent looks for the neighbours (e.g. spatial direct neighbours or optical direct ones and etc.) and connects to them. After that the analytical agent carries out



(a) (b) (c) (d)

Figure 5: The behaviour of the state variables q_n^i of the coupled system (1) with $m = 7$: **(a)** The case "only 2 agents from 7 are attacked"; **(b)** The case "only 3 agents from 7 are attacked"; **(c)** corresponds to (a), execution of the distributed plan 0; **(d)** corresponds to (b), execution of the distributed plan 1.

the negotiation session. As a result its state variable obtains the predefined values that is recognized by algorithmic agent, i.e. the state "0" corresponds to the plan "0" and the state "1" corresponds to the plan "1". The collectively accepted plan should be executed, after that the algorithmic agent perceives the next local sensor data, i.e. the whole cycle is repeated. Spatial formation, that the agents are moved in, is obtained by selecting different neighbour agents for increasing or decreasing the distance. **Plan 0**. In the first plant every agent attempts to keep a distance with only one neighbour agent. In the first phase it determines whether the selected agent is free. If an answer is positive the agent connects to it and then changes a status from free to busy. **Plan 1**. The second distributed plan is based on the symmetrical properties of regular polygons. All sides of such a polygon equal each other and circumscribed circle. Therefore as the local rule of an agent we can determine keeping the equal distance with one leading agent, that presents the center of group, and with two direct neighbours. The corresponding spatio-temporal patterns and the temporal behaviour of the state variables q_n^i are shown in Figure 5.

8 Conclusion

Coordination and decision making within distributed system without centralized elements can be performed using simple dynamical systems. Advantage of this approach is evident if to consider the nano- and biosystems that do not have complex computational devices, but possess different natural dynamics systems. Using this approach, the transferred information within a distributed system can be efficiently coded and moreover does not carry the global information about the whole system.

Security and privacy in the network using the suggested approach can be essentially improved if to encode the collective decisions not only by equal states as e.g. "all states equal one (1-1-1...)" or "all states equal zero (0-0-0...)", but also to encode by the mixed states (e.g. 0-1-0-1-1...). In this case a craker raiding into the network will get only local information about two neighbours that is senseless without other states of the group.

Our last remark concerns a phenomenon of the swarm intelligence from the viewpoint of synergetics. This phenomenon can be considered on the different abstraction levels. On the macroscopic level the group intelligence consists in the possibility to process the information perceived from different areas being accessible to the whole system, to coordinate the activity of separate agents in compliance with needs of overall system, to build new algorithms of distributed information processing. As pointed out by some authors the collective behaviour is not simply the sum of each participant's behaviour, substantially it emerges on the society level.

This points to existence of the social laws acting in the group on mesoscopic level. The question is how these social laws do arise in the group ? On the microscopic level every agent can be represented in a sense as consisting of different "internal" components. It is not only the separate structural or functional components but also their different combinations. From the viewpoint of synergetics the agent's "internal" components interacting on the microscopic level cause thereby the social law on mesoscopic level. The arisen social laws, influencing backwards on the behaviour of every agent, lead finally to the phenomenon of the swarm intelligence on the macroscopic level.

These ideas lead to the following conclusions. Firstly the social law acting in the group is nowhere contained in explicit form, it is always dynamically generated. It means that this law can not be extracted from the behaviour of separate agent. Secondly in order to modify the social law i.e. the macroscopic group intelligence it needs to modify the interaction between the internal agent components on the microscopic level. This can be distinctly seen on the simulation, where every agent is able to move in the four directions on the plane and to keeps the determined distances to neighbours. These abilities at the agents, composed into the group, are not changed. But on the base of communications the agents coordinate own activities and hereupon they can rationally react to the distributed influence directed on the whole group. Correspondingly modifying the communication, one can change this collective response, i.e. their swarm intelligence.

References

[1] T. T. Toth-Fejel, Agents, assemblers, and ANTS: scheduling assembly with market and biological software mechanisms, *Nanotechnology*, Vol. 11, 133-137, 2000.

[2] R. Stracke, K. J. Böhm, J. Burgold, H.-J. Schacht & E. Unger, Physical and technical parameters determining the functioning of a kinesin-based cell-free motor system, *Nanotechnology*, Vol. 11, 52-56, 2000.

[3] S.-T. Huang& T.-J. Liu, Self-stabilizing 2 m -clock for unidirectional rings of odd size, *Distrib. Comput.*, Vol. 12, 41-46, 1999.

[4] L. Ekenberg, The Logic of Conflicts between Decision Making Agents, *Logic Computat.*, Vol. 10, No. 4, 583-602, 2000.

[5] T. Sandholm, K. Larson, M. Andersson, O. Shehory & F. Tohmé, Coalition structure generation with worst case guarantees, *Artificial Intelligence*, Vol. 111, 209-238, 1999.

[6] I. Gerlovin, V. Ovsyankin, B. Stroganov & V. Zapasskii, Coherent transients in semiconductor nanostructures as a basis for optical logical operations, *Nanotechnology* Vol. 11, 383-386, 2000.

[7] D. Bagon, J. Kempe, D. A. Lidar, K. B. Whaley & D. P. DiVincenzo, Encoded universality in physical implementations of a quantum computer. *Preprint quant-ph/0102140* at http://xxx.lanl.gov.

[8] D. P. DiVincenzo, The physical implementation of quantum computation, *Preprint quant-ph/0002077* at http://xxx.lanl.gov.

[9] H. Haken, *Advanced Synergetics*, Springer Verlag, Berlin, Heidelberg, New York, Tokyo, 1983.

[10] G. Weiss, *Multiagent systems. A modern approach to distributed artificial intelligence*, MIT Press, 1999.

[11] K. Kaneko, *Theory and application of coupled map lattices*, (John Willey & Sons. Chichester, New York, Brisbane, Toronto, Singapore, 1993)

[12] N. Oswald, M. Becht, T. Buchheim, P. Burger, G. Hetzel, G. Kindermann, R. Lafrenz, M. Schanz, M. Schulé & P. Levi, CoPS-Team description, *RoboCup 2000*, Melbourne, 2000.

[13] S. Wiggins, *Introduction to applied nonlinear dynamical system and chaos*, Springer Verlag, New York, Heidelberg, Berlin, 1990.

[14] P. Levi, M. Schanz, S. Kornienko & O. Kornienko, Application of order parameter equation for the analysis and the control of nonlinear time discrete dynamical systems *Int. J. of Bifurcation and Chaos* Vol. 9, No. 8, 1619-1634, 1999.