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Emotional Intervention on Stigmergy Based Foraging Behaviour of Immune Network Driven Mobile Robots

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1. Introduction

Social insects are simple organisms capable (separately) of very limited activities with a view to intelligent behaviour. Each of them performs a local task unaware both of the behaviour of the others and of the implementation of the global task. However in groups, they possess some degree of intelligence, that allows them to perform extremely complex tasks. These achievements of social insects are due to the phenomenon of stigmergy - a powerful way to coordinate activity over both time and space. The concept of stigmergy has been introduced by the French entomologist Pierre-Paul Grassé in the 1950s during his studies of nest-building behaviour of termites (Grassé, 1959). Stigmergy is derived from the roots "stigma" (goad) and "ergon" (work), thus giving the sense of "incitement to work by the products of work" (Beckers et al., 1994).

Termite nest construction practices are an example of stigmergy. When termites start to build a nest, they impregnate little mud balls with pheromone and place them on the base of a future construction. Termites initially put mud balls in random places. The probability of placing a mud ball in a given location increases with the presence of other mud balls, i.e. with the sensed concentration of pheromone (positive feedback). As construction proceeds, little columns are formed and the pheromone near the bottom evaporates (negative feedback). The pheromone drifting from tops of columns, located near each other, causes the upper parts of the columns to be built with a bias towards the neighboring columns and to join with them into arches (typical building forms).

Corpse-gathering behaviour in ant colonies is another example of a functional and easy coordination through stigmergy. In this case the stigmergic communication is not realized through pheromones but through the corpses themselves. The insects put the corpses of dead nestmates together in a cemetery which is far from the nest. The ants pick ant corpses up, carry them about for a while, and drop them. It seems that ants prefer to pick up corpses from a place with small density of corpses and drop them to a place with higher density. In the beginning there exist a lot of single or small clusters of corpses, but as the time goes on the number of clusters decreases and their size grows up. At the end the process results in the formation of one (or two) large clusters. As it is evident from the two described examples, the ants do not control the overall performance, but rather the environment "puppeteer", the structure that eventually emerges, guides the process.

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Stigmergy is an indirect means of communication between multiple agents, involving modifications made to the environment. The agents are programmed so that they obey a simple set of rules and recognize local information to perform a small task. The agent carrying out its task, makes changes in the environment, which stimulates another (or the same) agent to continue working on the task. The environment itself acts as a shared external memory in the context of the system as a whole. The mechanism of stigmergy, combined with environmental physics, provides the basic elements of self-organization. *Self-organization* is a set of dynamical mechanisms whereby structures appear at the global level of a system as a result from interactions among its lower-level components (Bonabeau et al., 1997). However, the relationship between local and global types of behaviour is not easy to understand and small changes at a local level might result in drastic and sometimes unpredictable changes at the global level. Four basic ingredients and three characteristic features (signatures) of self-organization have been identified. The ingredients are: *positive feedback*, *negative feedback*, *amplification of fluctuations* and presence of *multiple interactions*; the signatures are: creation of *spatiotemporal structures* in an initially homogeneous medium, possible attainability of different *stable states*, and existence of parametrically determined *bifurcations* (Bonabeau et al., 1997; Holland & Melhuish, 1999).

Stigmergic concepts have been successfully applied to a variety of engineering fields such as combinatorial optimization (Dorigo et al., 1999; Dorigo et al., 2000), routing in communication networks (Di Caro & Dorigo, 1998), robotics, etc. In robotics, by means of simulated robot teams Deneubourg et al. (1990) have studied the performance of a distributed sorting algorithm (modelling brooding in ant colonies) based on stigmergic principles. Beckers et al. (1994) have extended Deneubourg's work, using physical robots that collect circular pucks into a single cluster, starting from a homogeneous initial environment. The robots have been equipped with two infra-red (IR) sensors, a gripper for pushing objects around, and a switching mechanism, which can sense the local concentration of objects only as below or above a fixed threshold. They have obeyed very simple behavioural rules and have required no capacity for spatial orientation and memory. Holland & Melhuish (1999) have proposed a very similar approach that examines the operation of stigmergy and self-organization in a homogeneous group of physical robots, in the context of the task of clustering and sorting objects (Frisbees) of two different types.

Stigmergy fits excellently into the behaviour-based robot control architecture, which is robust and flexible against the continually changing world. The real-world physics of the environment may be a critical factor for a system level behaviour to emerge. Simulation can provide a picture of possibilities for emergent behaviour. But the use of simulation means that the system is not "grounded" and is unable to exploit the real world physics of the environment. It is for this reason that some authors (Beckers et al., 1994; Holland & Melhuish, 1999) have chosen to implement stigmergic mechanisms directly to behaviour-based robots rather than to undertake any preliminary simulation studies. However, the evolutionary simulation is perhaps the best methodology for the moment for investigating stigmergic phenomena in general, as the real experiments are expensive, time consuming and destructive.

Experiments, similar to those, reported by Beckers et al. (1994), have been repeated in a simulated environment with one robot working alone and two robots working simultaneously in Ref. (Tsankova & Georgieva, 2004). Stigmergy based foraging robots need random movements in order to ensure exploration of all the places of the arena within a

reasonable period of time (Beckers et al., 1994). The problem to solve here is to find a way of speeding up the foraging process, because random movements make the process of formation of the final pile time consuming. Placing simulated detectors for object concentration in order to enhance the perceptive capabilities of the robots is a way of avoiding the loss of time due to wondering in an area without objects, as suggested in the literature (Tsankova et al., 2005; Tsankova et al., 2007). The detectors determine the directions with the maximum and minimum (non-zero) concentrations of pucks (with respect to the robot). The final foraging time has been improved in Ref. (Tsankova et al., 2007) by using two artificial immune networks: one for the navigation control of foraging robots and the other for the object picking up/dropping behaviour. However, the way to be realized the proper detector for object concentration and the accelerating the foraging process - these are still open questons.

For speeding up the foraging process one more time, emotional intervention on the immune navigation control and the object picking up/dropping behaviour is proposed in this research work. It is implemented as a frustration signal coming from an artificial amygdala (a rough metaphor of the natural amygdala, which is situated deep in the brain centre and is responsible for emotions). In a number of studies it has been shown that the psychological factors in general and the emotional factors in particular can be correlated to certain changes in the immunological functions and defense mechanisms (Lazarus & Folkman, 1984; Azar, 2001), i.e. the immune system can be influenced by emotions. This provides a reason for the design of a mixed structure consisting of an innate action selection mechanism, represented by an immune network, and an artificial amygdala as a superstructure over it (Tsankova, 2001; Tsankova, 2007). Another emotional intervention, implemented as an advisor, is applied to the picking up/dropping behaviour mechanism. Depending on the level of frustration the advisor forces the robot, carrying an object, to retain or to drop the object when the robot encounters small or large clusters, respectively. That enhances the positive feedback from the stimulus and speeds up the formation of the final pile.

To illustrate the advantages of the proposed emotional intervention in stigmergy-based foraging behaviour, five control algorithms are simulated in MATLAB environment. They use (respectively): (1) random walks; (2) purposeful movements based on enhanced perception of object concentration; (3) immune network based navigation; (4) emotionally influenced immune network based navigation; and (5) emotional intervention on an immune navigator and on the robot's picking up/dropping behaviour. The comparative analysis of these methods confirms the better performance of the last two of them in the sense of improving the speed of the foraging process.

2. The Task and the Robots

The basic effort in this work is directed toward developing a system of two simulated robots for gathering a scattered set of objects (pucks) into a single cluster (like the corpse-gathering behaviour of ants) and also toward speeding up the foraging process in comparison with the results of similar experiments, reported in the literature. To achieve this task by stigmergy, a simulated robot is designed to move objects that are more likely to be left in locations where other objects have previously been left. The robot is equipped with a simple threshold mechanism - a gripper, able to pick up one puck. An additional detector for puck concentration is used to determine the directions (with respect to the robot) with maximum and minimum (non-zero) concentrations of pucks (Tsankova et al., 2005). This information is

needed to prevent the random walks and to speed up the clustering process. The robots have to pick up pucks from places with small concentration and drop them at places with high concentration of pucks. Five methods of stigmergy based controls are discussed. The first method relies on random walks and codes the stigmergic principles in simple rules with fixed priorities (Beckers et al., 1994; Tsankova & Georgieva, 2004). The other four methods are characterized with enhanced sensing of puck concentration and include (respectively): (1) simple rules with fixed priorities (Tsankova et al., 2005), (2) an immune network for navigation control (Tsankova et al., 2005; Tsankova et al., 2007), (3) emotionally influenced immune network based navigation, and (4) emotional intervention on an immune navigator and on the picking up/dropping behaviour mechanism. The aim is to evaluate the performance of the robots equipped with the above mechanisms and controls in simulations. Before starting each run, 49 pucks are placed in the form of a regular grid in the arena, as shown in Fig.12a. At the beginning of each of the experiments, the robots start from a random initial position and orientation. Every minute of runtime, the robots are stopped, the sizes and positions of clusters of pucks are recorded, and the robots are restarted. The experiment continues until all 49 pucks are in a single cluster. A cluster is defined as a group of pucks separated by no more than one puck diameter (Beckers et al., 1994).

The geometry of robots is shown in Fig.1a, where the radii of the robot and the puck are $R = 0.036$ m and $R_{\text{puck}} = 0.015$ m, respectively. Each robot carries a U-shaped gripper with which it can take pucks. The robots are run in a square area $1.5\,\text{m} \times 1.5\,\text{m}$. The robots are equipped with simulated obstacle detectors (five infra-red sensors) and a simulated microswitch, which is activated by the gripper when a puck is picked up. Obstacle detectors are installed in five directions, as shown in Fig.1b. They can detect the existence of obstacles in their directions (sectors S_i, $i = 1,2,...,5$), and the detecting range of sensors is assumed to be equal to the diameter of the robot. The detectors for puck concentration are located at the same position as the obstacle detectors (Fig.1b). The simulated detector for concentration of pucks can enumerate the pucks (but does not discriminate clusters), which are disposed in the corresponding sector S_i with a range, covering the entire arena. The readings of the detectors for puck concentration are denoted by C_i, $i = 1,2,...,5$. They are normalized as

$$C_i = N_i^{puck} \Big/ \sum_{j=1}^{5} N_j^{puck}, \quad i = 1,2,...,5, \tag{1}$$

where N_i^{puck} is the number of pucks, located in the sector S_i.

For the sake of simplicity of simulation the following assumptions in the design of the gripper, the microswitch and the pucks are used (Tsankova & Georgieva, 2004):

- A puck will be scooped only when it fits neatly inside the semicircular part of the gripper.
- If part of a puck is outside of the gripper, the puck will not be scooped, it will not be pushed aside, and the robot will pass across it.
- When the microswitch is activated, the puck may be dropped either on an empty area or on other pucks.
- The pile may grow in height.

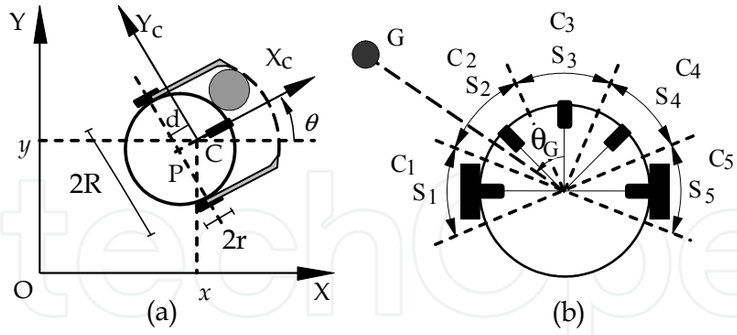


Figure 1. Autonomous mobile robot used in simulations

3. The Algorithms

The five algoritms, mentioned above, are described in more details in this section. The last two of them are the proposed innovations, including an improvement of the robot's navigation and puck picking up/dropping behaviour by introducing an artificial emotional mechanism. The first three algorithms have already been proposed in the literature, and the experiments based on them (implemented in this work) serve as a basis for comparison with the outcomes of the proposed innovations.

I. Stigmergy with random walks

The following rule set is inspired by Ref. (Beckers et al., 1994) and describes the basic behaviours of robots (Tsankova & Georgieva, 2004):

(1) ***If*** (there is not a puck in the gripper) & (there is a puck ahead) ***then*** take one puck in the gripper.

(2) ***If*** (there is one puck in the gripper) & (there is a puck ahead) ***then*** drop a puck, go backward for a while (t_{backward}) and turn at a random angle.

(3) ***If*** there are no pucks ahead ***then*** go forward.

(4) ***If*** there is an obstacle (wall or another robot) ahead ***then*** avoid the obstacle (turn at a random angle and go forward).

Moving in a straight line is the robot's default behaviour, which is executed when no sensor is activated. This behaviour continues until an obstacle is detected or the microswitch is activated (pucks are not detected as obstacles). When the robot detects an obstacle it executes the obstacle avoidance behaviour. On the spot it turns away from the obstacle at a random angle until detectors no longer find out the obstacle, and then goes forward (Beckers et al., 1994). If the robot carries a puck when it encounters the obstacle, the gripper will retain the puck during the turn. The execution of the obstacle avoidance behaviour suppresses the puck dropping one. The threshold of the gripper allows it to take only one puck; more pucks force the microswitch to trigger the puck dropping behaviour. The robot releases the puck from the gripper, goes backwards for a while, and then turns at a random angle, after which returns to its default behaviour and moves forward in a straight line.

II. Stigmergy with enhanced sensing of object concentration

The following set of rules describes the robot's behaviours, when the puck concentration is taken into account (Tsankova et al., 2005):

(1) ***If*** (there is not a puck in the gripper) & (there is a puck ahead) ***then*** take one puck in the gripper.
(2) ***If*** (there is one puck in the gripper) & (there is a puck ahead) ***then*** drop a puck and go backward for a while (t_{backward}).
(3) ***If*** (there is not a puck in the gripper) & (there are no pucks ahead) ***then*** follow the direction, corresponding to the *minimum* (non-zero) reading of the detectors for puck concentration.
(4) ***If*** (there is one puck in the gripper) & (there are no pucks ahead) ***then*** follow the direction, corresponding to the *maximum* reading of the detectors for concentration of pucks.
(5) ***If*** there is an obstacle (wall or another robot) ahead ***then*** avoid the obstacle (turn on the obstacle avoidance behaviour).

When no obstacle detector is activated, the robot executes a goal following behaviour with an artificial goal G (Fig.1b) corresponding to the place with the maximum or minimum concentration of pucks, depending on the presence or absence of a puck in the gripper, respectively. The puck concentration detectors determine the direction of the artificial goal. If all pucks are disposed behind the robot, the low-level control makes the robot turn until a puck concentration detector becomes active. The goal following behaviour continues until an obstacle is detected or the microswitch is activated. The obstacle avoidance and the puck dropping behaviour are the same as the behaviours described in the previous algorithm (Algorithm I).

III. Stigmergy with an immune navigation control

The immune networks for this and for the next control algorithms use enhanced sensing of object concentration. In conformity with the immune navigation control, the set of rules of Algorithm II (from rule (1) to rule (5)) is modified so that *the first two rules remain unchanged*, and the other three are substituted by the following rule (3a) (Tsankova et al., 2005; Tsankova et al., 2007):

(3a) ***If*** (there are no pucks ahead) *OR* (there is an obstacle ahead) ***then*** turn on the collision free goal following behaviour, realized by an *artificial immune network*.

If there is one puck in the gripper, the direction of the goal G is the direction corresponding to the sector with the maximum number of pucks, and if there is no puck in the gripper – the direction with the minimum puck concentration. The immune network implements a collision-free goal following behaviour.

IV. Stigmergy with an emotionally influenced immune navigation control

An artificial emotion mechanism (EM1 in Fig.6) is proposed as a superstructure over the immune network based navigator. It may influence the decision-making mechanism of the immune network, modulating the dynamics of antibody selection that is described in detail in Sections 5 and 6. The control algorithm is the same as Algorithm III, but the rule (3a) is replaced by the following rule (3b):

(3b) ***If*** (there are no pucks ahead) *OR* (there is an obstacle ahead) ***then*** turn on the collision free goal following behaviour, realized by an *emotionally influenced* immune network.

It is expected that the emotional intervention will improve the robot's collision-free goal following behaviour, and therefore it will speed up the foraging process.

V. Stigmergy with two artificial emotion mechanisms

The first of the two artificial emotion mechanisms (EM1) serves for the emotional intervention on the immune navigator as it was described in Algorithm IV. The innovation

here is the second artificial emotion mechanism (EM2) used as an advisor of the puck picking up/dropping mechanism by the regulation output $\gamma^{\text{prohibit}}_{\text{puck dropping}} = 0;1$ (Fig.7). The following set of rules describes the robot's behaviours, when the two emotion mechanisms are taken into account:

(1) ***If*** (there is not a puck in the gripper) & (there is a puck ahead) ***then*** take one puck in the gripper.

(2a) ***If*** (there is one puck in the gripper) & (there is a puck ahead) & ($\gamma^{\text{prohibit}}_{\text{puck dropping}} = 0$) ***then*** drop a puck and go backward for a while (t_{backward}).

(2b) ***If*** (there is one puck in the gripper) & (there is a puck ahead) & ($\gamma^{\text{prohibit}}_{\text{puck dropping}} = 1$) ***then*** retain the puck and turn on the collision free goal following behaviour, realized by *an emotionally influenced immune network*.

(3) ***If*** (there are no pucks ahead) *OR* (there is an obstacle ahead) ***then*** turn on the collision free goal following behaviour, realized by *an emotionally influenced immune network*.

The emotional advisor of the puck picking up/dropping mechanism in fact influences on the puck dropping behaviour only, as the robot releases the puck under a large frustration level (regulation output of EM2 is $\gamma^{\text{prohibit}}_{\text{puck dropping}} = 0$), and retains the puck when the frustration is small ($\gamma^{\text{prohibit}}_{\text{puck dropping}} = 1$) (Fig.7). The first case corresponds to large puck density, detected by the sensors, and the second – to small density. Due to the dynamics of the amygdala's model (5), the frustration's threshold is different, depending on the direction of robot's movement – towards a larger cluster or in the opposite direction. It is expected that this will enhance the positive feedback from the stimulus (the maximum cluster of objects) and will improve the foraging process in the vicinity of large clusters.

4. Immune Networks

4.1 Biological and artificial immune networks

The human body maintains a large number of immune cells – *lymphocytes*, mainly *T-cells* and *B-cells*. When an *antigen* (a foreign body) invades the human body, only a few of these immune cells can recognize the invader. The *idiotypic network hypothesis*, proposed by Jerne (1974), is based on the concept that lymphocytes are not isolated, but communicate with each other through interaction among antibodies. *B-lymphocytes* have specific chemical structure and produce "Y" shaped *antibodies*. The antibody recognizes an *antigen* like a *key and lock relationship*. The structure of the antigen and the antibody is shown in Fig.2, where the part of the antigen recognized by the antibody is called *epitope*, and the part of the antibody that recognizes the corresponding antigen determinant is called *paratope*. The antigenic characteristic of the antibody is called *idiotope*. Antibodies stimulate and suppress each other by the idiotope-paratope connections and thus form a large-scaled network.

The idiotypic network theory is usually modelled with differential equations simulating the dynamics of lymphocytes. Farmer et al. (1986) have first suggested an abstracted mathematical model of Jerne's *immune network theory*. In robotics Ishiguro et al. (1995b) and Watanabe et al. (1999) have developed a dynamic decentralized behaviour arbitration mechanism based on immune networks. In their approach "intelligence" is expected to emerge from interactions among agents (competence modules) and between a robot and its

environment. A collision-free goal following behaviour has been performed in Ref. (Ishiguro et al., 1995b), and a garbage-collecting problem taking into account self-sufficiency – in Ref. (Watanabe et al., 1999). More detailed surveys of artificial immune systems and their applications can be found in Refs. (Dasgupta & Attoh-Okine, 1997; Garrett, 2005). The description of the dynamics of the antibody selection mechanism and the artificial immune navigator, as they have been presented in Ref. (Tsankova et al., 2007), follows below.

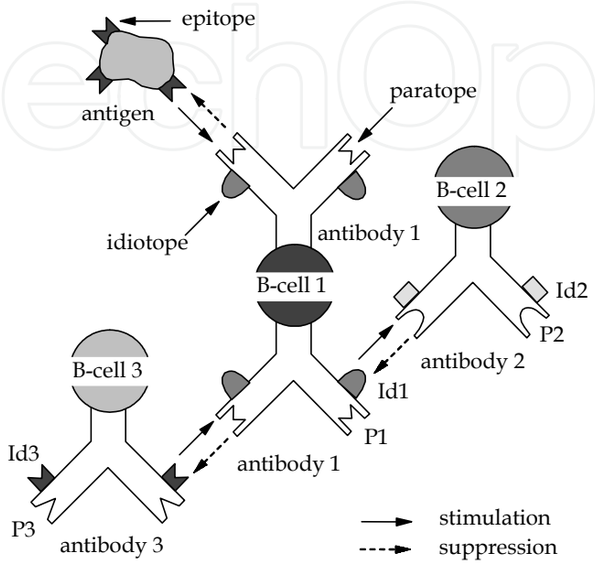


Figure 2. Structure of immune network (Ishiguro et al., 1995b)

4.2 Dynamics of antibody selection mechanism

Consider a goal following and obstacle avoidance navigation task. In such a situation, for example, the distance and direction to the detected obstacle or to the goal work as an antigen, the competence module (simple behaviour/action) can be considered as an antibody, and the interaction between modules is presented as stimulation/suppression between antibodies. The concentration $a_i(t)$ of the i-th antibody is calculated as (Ishiguro et al., 1995a; Ishiguro et al., 1995b):

$$\frac{da_i(t)}{dt} = \left(\frac{1}{N} \sum_{j=1}^{N} m_{j,i} a_j(t) - \frac{1}{N} \sum_{k=1}^{N} m_{i,k} a_k(t) + m_i - k_i \right) a_i(t), \tag{2}$$

where N is the number of the antibodies, $m_{j,i}$ and m_i denote affinities between the antibody j and the antibody i, on the one hand, and the antibody i and the detected antigen, respectively. The first and the second terms on the right hand side denote the stimulation and suppression coming from other antibodies, respectively. The third term represents the stimulation coming from the antigen, and the fourth term k_i - the natural death. The affinity coefficients $m_{j,i}$ and m_i are calculated by (Ishiguro et al., 1995b):

$$m_{j,i} = \alpha \sum_{k}^{L} I_j(k) \oplus \overline{P_i(k)}, \qquad m_i = \beta \sum_{k}^{L} E(k) \oplus \overline{P_i(k)}, \tag{3}$$

where α and β are positive constants, $\oplus$ represents the exclusive-or operator, L is the length of the paratope, the idiotope and the epitope, written as binary strings. $I_j(k)$, $P_i(k)$ and $E(k)$ represent the k-th binary value in the idiotope string of the antibody j, the paratope string of the antibody i, and the epitope string, respectively. If the concentration of the antibody exceeds a priori given threshold, the antibody is selected and its corresponding behaviour becomes active towards the world.

4.3 Artificial immune navigator

In this work by "navigator" will be denoted the collision-free goal following behaviour control. The obstacle detectors give binary information 1/0 about the existence or absence of obstacles in their range, respectively. On the basis of the readings of the puck concentration detectors C_i, $i = 1,2,...,5$ a simulated goal detector can recognize the direction of the goal (maximum/minimum puck heaping) at any position of the obstacle detectors. In the case, in which there is a puck in the gripper, the simulated goal detector responds with 1 to the direction of $C_{\max} = \max(C_i)$ and with 0 to the other four directions. When the robot does not carry a puck, it responds with 1 to the direction of $C_{\min} = \min(C_i)$ and 0 to the rest. Therefore, the robot's simulated detectors discover two types of antigens (obstacle-oriented antigens and goal-oriented ones), and each antigen has a five-bit epitope. The antigens inspire the same two types of antibodies. The antibody's paratope (Fig.3) corresponds to the desirable condition (the precondition, which has to be fulfilled before the activation of the antibody), and its idiotope - to the disallowed antibodies (the antibodies which are impossible or undesirable when the condition of the paratope and its corresponding action are implemented) (Ishiguro et al., 1995b). For mobile robot navigation a simple immune network with 12 a priori prepared antibodies is used (Tsankova & Topalov, 1999; Tsankova et al., 2005) (Fig.4). The first six antibodies are stimulated by obstacle-oriented antigens, and the other six – by goal-oriented ones. Their actions are: move forward (Front), turn right (RS, RM), turn left (LS, LM), move backward (TurnBack). In Fig.4 the goal-oriented paratopes are not presented as binary strings, as they are expressed in calculations, for the sake of the easier explanaion of the network. For example, $G \in S_1$ is expressed in calculations by $1\,0\,0\,0\,0$ and denotes that the goal (G) appears in the sector S_1 of the goal detector, and $G \in$ none - is expressed by $0\,0\,0\,0\,0$, which shows that the goal is not discovered in the five sectors of the goal sensor, i.e. it is behind the robot. The symbol # denotes that the condition can be taken as either 0 or 1, i.e. it can be considered not so important information. Therefore, in (3), when $P_i(k) = \#$ or $I_j(k) = \#$ it determines that $I_j(k) \oplus \overline{P_i(k)} = E(k) \oplus \overline{P_i(k)} = 0.25$. The idiotope includes disallowed antibodies for a situation, in which the paratope condition is fulfilled. For example, the paratope of antibody 9 shows that the goal is discovered in front of the robot in the sector S_3 and the corresponding action is "move forward" (Front). This behaviour will be impossible, if there is an obstacle in front of the robot, i.e. if the obstacle detectors react with the string $\#\#1\#\#$, which unites the paratopes of the antibodies 2, 3, 4, 5 and 6, and they are considered to be disallowed. The readings of the puck concentration detectors form the goal-oriented antigens. For example, if the maximum puck heaping has occurred in the sector S_4, i.e.

$C_{max} \in S_4$, and the minimum - in S_1 ($C_{min} \in S_1$), then the epitope string will be $0\,0\,0\,1\,0$ or $1\,0\,0\,0\,0$, corresponding to the availability or absence of a puck in the gripper. In Fig.4 the stimulation connections from the idiotopes to the corresponding paratopes are shown by arrows.

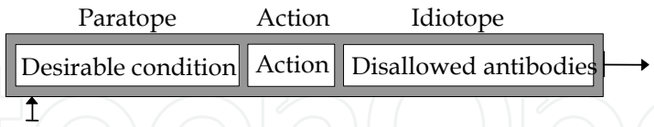


Figure 3. Antibody (Ishiguro et al., 1995b)

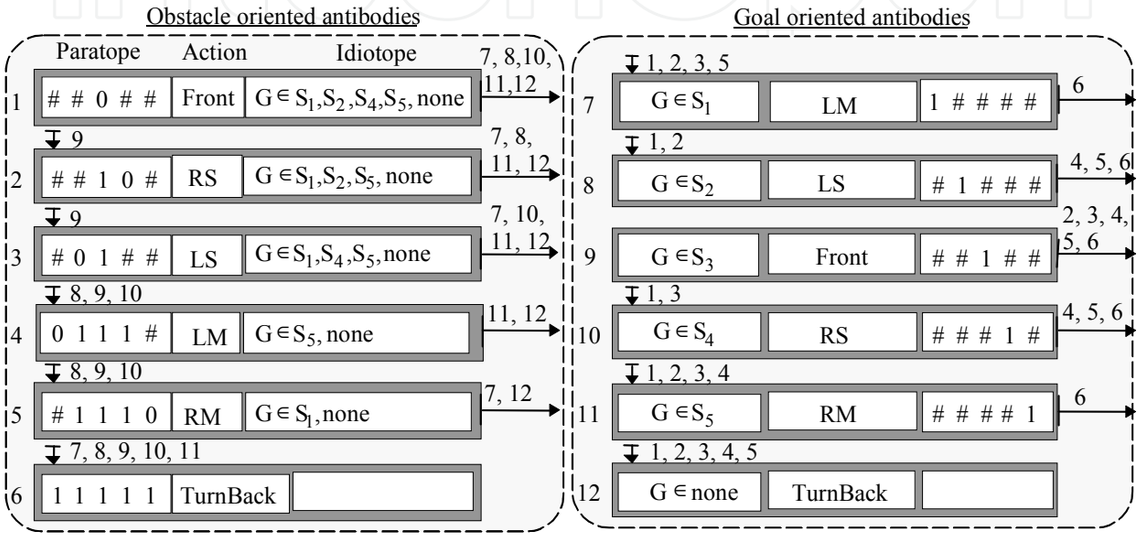


Figure 4. Immune network for collision free goal following behaviour (Tsankova & Topalov, 1999; Tsankova et al., 2005)

For each particular situation detected by sensors, only one of all antibodies wins (in conformity with (2) and (3)) and its action becomes the target behaviour (direction of movement) for the mobile robot. In this work the weight of the two types of behaviour – obstacle avoidance and goal following - is expressed by additional multiplication of the coefficients m_i of the obstacle-oriented antibodies (from 1 to 6) and the goal-oriented antibodies (from 7 to 12) by the weight coefficients k_{goal} and k_{obst}, respectively:

$$m_i = k_{obst}\beta\sum_{k=1}^{L} E(k) \oplus \overline{P_i(k)}, \quad i = 1,2,...,6; \quad m_i = k_{goal}\beta\sum_{k=1}^{L} E(k) \oplus \overline{P_i(k)}, \quad i = 7,8,...,12. \qquad (4)$$

5. Emotional Intervention on Immune Network

The emotional intervention on an artificial immune network is inspired by the interactions between immune and emotional systems in living organisms, which have been developed during their struggle to cope with continually changing internal and external environments through hundred millions of years. Today *psychoneuroimmunology* investigates the link between bi-directional communication among the nervous, endocrine, and immune systems and its implications for physical health. In this Section follows: an overview of the

definitions of emotions, models of emotions and their applications, to the purpose of choosing a proper computational model for influence on the artificial immune network designed in the previous Section. At the end, the way of integrating the selected model into the equations of dynamics of antibody selection is described.

5.1 Emotions, models, and applications

Emotion is a key element of the adaptive behaviour, increasing the possibility of survival of living organisms. Science is still looking for a complete definition of emotion. All feelings (states) that affect the survival goal of an agent are called motivational states, such as hunger, thirst, pain, sometimes fear, etc. (Bolles & Fanselow, 1980). Emotions, among other feelings, can change the facial expressions (Descartes, 1989). According to Ekman (1992), there exist six basic emotions: anger, fear, sadness, joy, disgust, and surprise.

One of the most extensively developed low-level neurological models of emotions is that of the amygdala (LeDoux, 1996), especially functioning as a classical fear system of the brain. There exist models that have developed a pure physiological simulation of emotions (emotions described in terms of their physiological reactions) (Picard, 1997), and others that deal with the interactions between emotions (or motivational states), for example, fear and pain (Bolles & Fanselow 1980). The event appraisal models of emotions (Ortony et al. 1988; Rosman et al., 1990) are higher-level psychological models developed to understand the link between events and emotions.

All of the above mentioned and various other computational models of emotions have found application in robotics (Mochida et al., 1995; Breazeal, 2002), affective computing (Picard, 1997), believable ("life-like") agents (Bates, 1992) etc. In robotics Mochida et al. (1995) have proposed a computational model of the amygdala and have incorporated it into an autonomous mobile robot with an innate action selection mechanism based on Braitenberg's architecture No.3c (Braitenberg, 1984). After a brief overview on emotions and their models, the computational version of an amygdala's model seems to be the most convenient for the purposes of the task treated here. A short description of this model follows below.

5.2 Model of the amygdala as an artificial emotion mechanism

The *amygdala* is responsible for the emotions, especially for the most fundamental among them - the fear. It is situated deep in the brain's centre. When the amygdala feels a threat, it mobilizes the resources of the brain and the body to protect the creature from damage. Sensor information obtained by receptors firstly enters the *thalamus*, and then forks into the cerebral *cortex* and the amygdala. Information processing in the cerebral cortex is fine-grained, that is why the signals from the cortex are so slow and refined, and provide detailed information about the stimulus. The signals coming from the thalamus are fast and crude, reaching the amygdala before the signals from the cortex, but providing only general information about the incoming stimulus. The coarse information processing accomplished in the amygdala requires less computing time compared to the one needed by the cortex, since the amygdala just evaluates whether the current situation is pleasant or not. This coarse but fast computation in the emotional system is indispensable for self-preservation of living organisms, which have to overcome the challenges of a continually changing world. The pathways that connect the amygdala with the cortex ("the thinking brain") are not symmetrical - the connections from the cortex to the amygdala are to a large extent weaker

than those from the amygdala to the cortex. The amygdala is in a much better position to influence the cortex. This is one of the reasons for which "the amygdala never forgets (LeDoux, 1996)" and psychotherapy is often such a difficult and prolonged process. Due to the above characteristics, it can be considered that the emotional system regulates activities in the cerebral cortex feed forwardly (Mochida et al., 1995).

In the computational model of the amygdala proposed by Mochida et al. (1995), the emotion of robots is divided into two states: *pleasantness* and *unpleasantness*, represented by a state variable called *frustration*. The neural network representation of this model is shown in Fig.5. Using sensory inputs the level of frustration is formulated as (Mochida et al., 1995):

$$f_{k+1} = \xi_1 \sum_{i=1}^{n} W_i S_i + (1 + \xi_2 \sum_{i=1}^{n} W_i S_i - b) f_k \ , \tag{5}$$

where f_k represents the frustration level of the agent at the moment k, ξ_1 and ξ_2 are coefficients, W_i denotes the weight parameter with respect to the obstacle detector S_i, and b is the threshold, which determines the patience for unpleasantness; n is the number of equipped obstacle detectors; In (5), the first and the second terms on the right hand side denote the frustration levels caused by the direct stimulation of the agent and the recently experienced relationship between the agent and the situation, respectively. The regulation output $\gamma = \gamma(f)$ of the emotional mechanism is determined here as:

$$\gamma = -[1 - e^{-2(f + b_\gamma)}] / [1 + e^{-2(f + b_\gamma)}], \tag{6}$$

where $f \leftarrow f_k$ is taken from (5), b_γ is a bias, and $\gamma \in [-1; 1]$ (Fig.5).

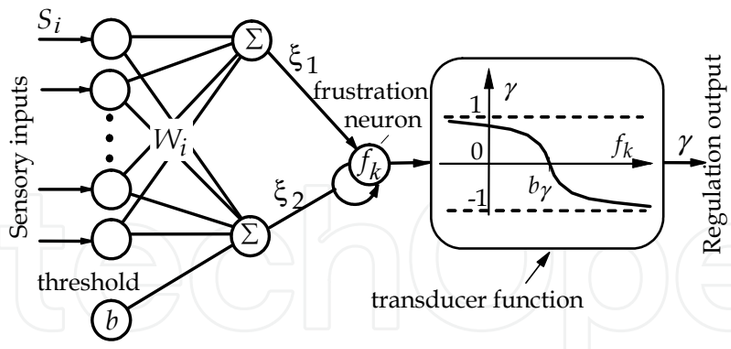


Figure 5. Model of amygdala (Mochida et al., 1995)

5.3 Emotionally influenced dynamics of antibody selection

The emotional intervention on the immune network, whose architecture is shown in Fig.4, can be implemented as a frustration signal coming from the computational model of an amygdala (Fig.5) and influencing the dynamics of the antibody selection mechanism. The regulation output γ of the amygdala is able to modulate different network parameters (affinity coefficients and natural death), or to influence directly the change of concentration of antibodies. Thus it can change the antibody-winner and the final behaviour of the robot.

In the particular navigation problem the emotional mechanism can merely affect the antibodies for goal following behaviour (from 7 to 12) by suppressing the rate of change of the concentrations of those antibodies. This can be obtained by modifying the equations from 7 to 12 of the system of differential equations (2) by multiplying together their right hand side (derivatives of concentrations) and the regulation output γ of the amygdala. Thus, the system of equations (2) is transformed as it follows (Tsankova, 2007):

$$\begin{aligned} \frac{da_i(t)}{dt} &= F_i(a(t), m_i, m_{ij}, k_i), \qquad i = 1,2,...,6, \\ \frac{da_i(t)}{dt} &= \gamma F_i(a(t), m_i, m_{ij}, k_i), \quad i = 7,8,...,12, \end{aligned} \tag{7}$$

where $F_i(.)$ is the right hand side of (2).

6. Emotional Intervention on Robot's Immune Navigator and on Puck Picking up/Dropping Mechanism

6.1 The navigator

The emotionally influenced immune navigator, proposed in Algorithms IV and V (Section 3), consists of: (1) an immune network (Fig.4) as a basic action selection mechanism; and (2) an artificial emotional mechanism – a model of an amygdala (Fig.5) as a superstructure over the immune network, which modulates the antibody selection. The model of an amygdala (5)-(6) weaves into the differential equations, describing the dynamics of antibody selection (2)-(4) in a way, similar to the one, described in Subsection 5.3. After a number of preliminary experiments with a navigator, which is based on the model (7), that model was modified as follows:

$$\frac{da_i(t)}{dt} = \gamma_{\text{nav}} F_i(a(t), m_i, m_{ij}, k_i) \text{ ,where } \quad \gamma_{\text{nav}} = \begin{cases} 1, & \text{if } \ i = 2,3,...,6, \\ \gamma, & \text{if } \ i = 1, \ i = 7,8,...,12, \end{cases} \tag{8}$$

The modification includes an emotional intervention on both the goal-oriented antibodies from 7 to 12 and the antibody 1, which executes a movement forward when there is not an obstacle in front of the robot. In the absence of obstacles the regulating output of the amygdala has a value of $\gamma = 1$, and thus it does not influence the dynamics of the immune network. However, in the presence of an obstacle, the selection of antibody 1 is manipulated by γ and the probability for this antibody to be selected on a system level (8) decreases. Therefore, in these cases the rotary motion, rather than the rectilinear forward motion is preferred. As a result, more flexible manoeuvring is expected in difficult situations, such as Π-shaped obstacles and narrow passages. A block diagram of the system "emotionally influenced immune navigator – mobile robot" is shown in Fig.6, where α is the "action" part of the antibody winner, and $\mathbf{v} = (v, \omega)$ is the target velocity vector.

The kinematics of a mobile robot with two driving wheels, mounted on the same axis, and a front free wheel is used in simulations (Fig.1a). The motion of the mobile robot is controlled by its linear velocity v and angular velocity ω. The trajectory tracking problem under assumption for "perfect velocity tracking" is posed as in Kanayama et al. (1990) and Fierro

& Lewis (1995). Details of this low-level tracking control are omitted due to the limited space here.

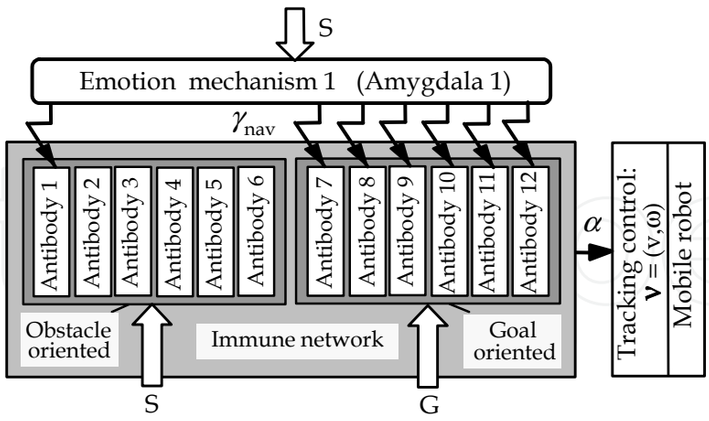


Figure 6. Block diagram of the system 'emotionally influenced immune navigator – mobile robot'

6.2 The puck picking up/dropping mechanism

The idea behind the emotional intervention on the puck picking up/dropping mechanism is to use the frustration threshold of a second amygdala EM2 (Fig.7), whose inputs are the sensor readings of puck concentration, in order to influence the puck dropping behaviour. If a robot with a full gripper collides with a puck ahead (or clusters of pucks), it will drop the puck only if the frustration of the amygdala EM2 exceeds a certain threshold. In the opposite case it will retain the puck and will continue moving in the same direction. Since the robot does not perceive the pucks as an obstacle, it does not go round them, but passes across them. It is assumed, that the matter in the robot's hand is a single puck or a very small cluster of pucks, since the frustration is below the threshold. So, the stigmergic process will rather benefit than be harmed by the destruction of the small cluster (if this occurs). Due to the dynamics of the amygdala's model, the frustration threshold is different, depending on the direction of the robot's movement – towards a larger cluster or in the opposite direction. The regulation output of EM2 generates the following signal:

$$\gamma_{\text{puck dropping}}^{\text{prohibit}} = \begin{cases} 0, & \text{if } \gamma \le 0, \\ 1, & \text{if } \gamma > 0. \end{cases} \tag{9}$$

where the values '0' and '1' mean 'permission' and 'prohibition' of the puck dropping behaviour, respectively. A block diagram illustrating EM2 is shown in Fig.7.

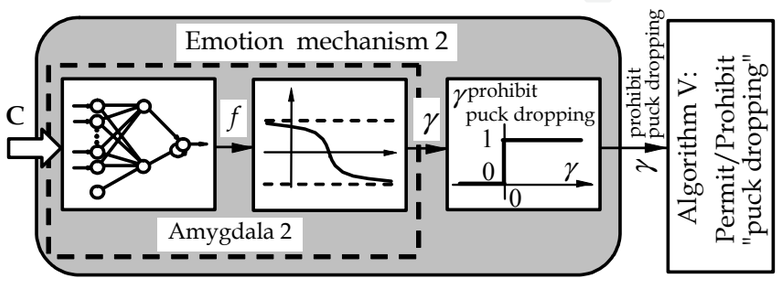


Figure 7. Block diagram of the emotional intervention on puck dropping behaviour

7. Simulation Results and Discussions

7.1 Simulation experiments with emotionally influenced navigator

The improvement of the navigation of a single robot should be aimed at increasing the reliability and the efficiency of work of the overall robot group in the puck foraging task. The simulation experiments in this Subsection emphasize the emotionally affected immune navigator; they make clear both the mechanism of action of amygdala's model and the way by which it influences the immune navigator; show the advantages of the mixed structure by a comparative analysis carried out between the proposed emotionally influenced immune navigator and the following control structures: (1) Braitenberg's vehicle No.3c with an emotional mechanism (Mochida et al., 1995), and (2) the immune network based navigator.

The simulation experiments were implemented in MATLAB environment with the sampling time set to $T_o = 0.01\,\mathrm{s}$. The parameters of the trajectory tracking controller were chosen to correspond to a critical dumping case (Kanayama et al., 1990), and the reference linear and angular velocities were $v_{\mathrm{ref}} = 0.3\,\mathrm{m/s}$ and $\omega_{\mathrm{ref}} = 0\,\mathrm{rad/s}$, respectively. The duration of the movement backward was $t_{\mathrm{backward}} = 0.75\,\mathrm{s}$. The parameters needed for modelling the dynamics of the antibody selection were heuristically determined as: $\alpha = \beta = 1$; $k_{\mathrm{obst}} = 1$ and $k_{\mathrm{goal}} = 0.4$; the death rate $k_i = 0.1$, $i = 1,2,...,12$; and the threshold for the antibody selection mechanism $a_{\mathrm{thresh}} = 0.33$. The following values for the angles of the immune network's "action" part were experimentally chosen: $Front = 0\,\mathrm{rad}$, $LS = -RS = 0.65\,\mathrm{rad}$, $LM = -RM = 1.4\,\mathrm{rad}$, and $Back = 1.4\,\mathrm{rad}$. The parameters of the amygdala's model have been investigated theoretically and experimentally in (Tsankova, 2001) and the values, determined as proper there, were used in this study, i.e.: $\xi_1 = 0.003$, $\xi_2 = 0.3$, $b = 0.12$, $b_\gamma = 5$ and $\mathbf{W} = (0.25 \;\; 0.75 \;\; 2.5 \;\; 0.75 \;\; 0.25)^{\mathrm{T}}$. The frustration signal was limited in accordance with its definition domain $f \in [f_{\min}; f_{\max}]$, where $f_{\min} = 0$ and $f_{\max} = 18$ (Tsankova, 2001).

The robot, controlled by the immune navigator without emotional intervention, was simulated, and the results from the simulation are shown in Fig.8. The symbols $*$, $\times$ and $\circ$ denote the goal position, as well as the initial and final position of the robot, respectively. The robot orientation with respect to the inertial basis is denoted by θ. The measuring units on the two axes of the robot's rectangular work area are metres. Different behaviours were obtained by suppressing some antibodies of the immune network shown in Fig.4. For example, obstacle avoidance behaviour (Fig.8a) was derived by suppressing the goal-oriented antibodies from 7 to 12, and for achieving wall following behavior (Fig.8b) the antibody 1 was additionally suppressed. As a result of suppressing the obstacle-oriented antibodies from 1 to 6, goal following behaviour was evoked (Fig.8c). When all 12 antibodies interacted (without any external inhibition) the resultant behaviour was a collision-free goal following behaviour (Fig.8d).

Fig.9a shows another simulation result of a robot with an immune navigator without emotional intervention. Although all antibodies interact without any external inhibition, the robot sometimes gets stuck in small corners, dead ends, and narrow passages. Fig.9b illustrates a better performance of the robot in the same environment, when it is equipped with the proposed emotionally affected immune navigator. On the basis of amygdala's

frustration level f the regulation output γ_{nav} influences the immune network by suppressing, stopping or reversing the goal following behaviour, and thus focuses the attention on the avoidance of obstacles in critical situations. The amygdala (in high frustration) stimulates wall following behaviour rather than obstacle avoidance (the antibody 1 is suppressed simultaneously with the goal following antibodies from 7 to 12) (Fig.6). This behaviour proves to be more successful than the obstacle avoidance in respect to increasing the probability for overcoming some closed-loop situations. For easier understanding of the effect of emotional intervention on the immune navigator, the transitions of the activity of frustration and the regulation output of the amygdala in the case of Fig.9b are calculated. The results are shown in Fig.10, where the letters from "A" to "J" correspond to those in Fig.9b. The frustration level increases when the robot reaches an impasse, and the goal following activity decreases. The robot could resign the goal pursuing. The maximum possible value of frustration $f_{\max} = 18$ (or near it) in the intervals "AB", "CD", "EF", "GH", and "IJ" corresponds to a "near-dead-end" situation (the obstacle is exactly between the robot and the goal, in front of the robot, in the role of a bracket) or a "narrow passage" situation.

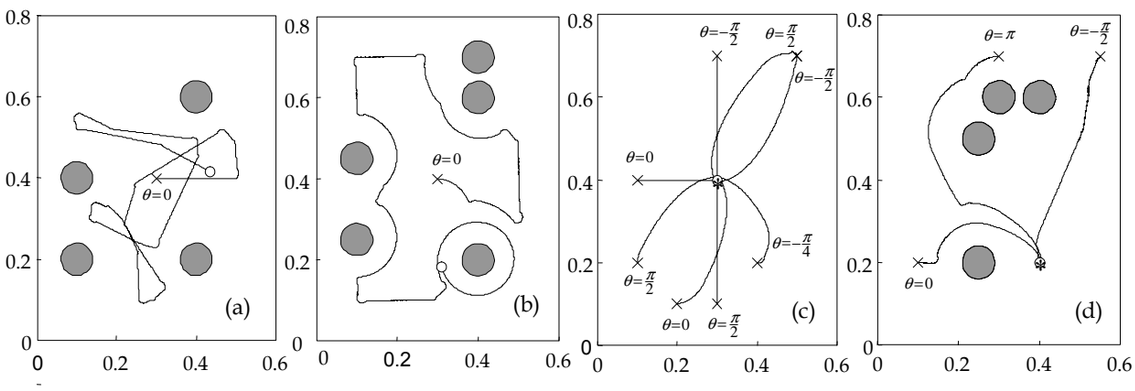


Figure 8. Obstacle avoidance (a), wall following (b), goal following (c), and collision-free goal following (d) behaviours

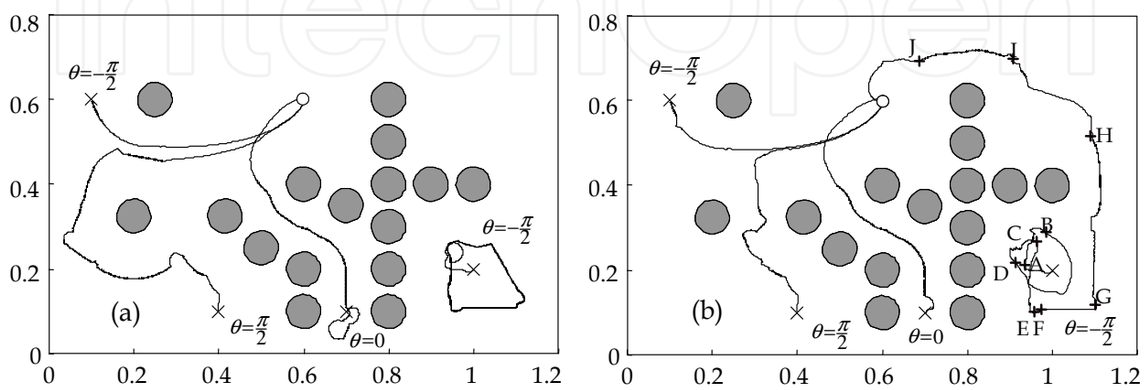


Figure 9. Immune navigator: (a) - independently acting, and (b) - emotionally influenced

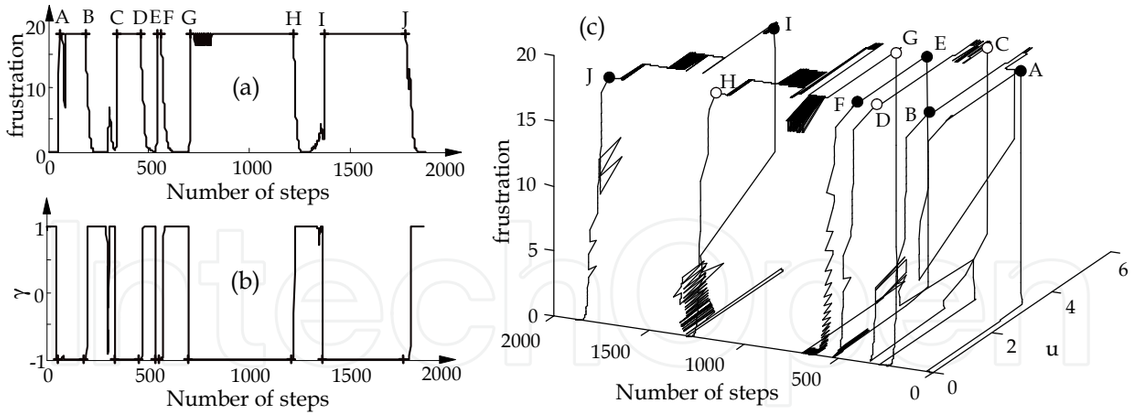


Figure 10. Transition of frustration/regulation output of amygdala used in simulations in Fig.9b

Consider the weighted sum of sensor inputs of the amygdala's model (5) $u(t) = \sum_{i=1}^{n} W_i S_i(t)$ (or $u(t) = \sum_{i=1}^{n} W_i C_i(t)$ for the case of EM2). Since the sensor signals are normalized between 0 and 1 inclusive ($S_i = 0;1$ ($C_i \in [0;1]$), $i = 1,...,5$), then $u \in [0; U_{\max}]$, where $U_{\max} = \sum_{i=1}^{n} W_i$.

The change of the frustration signal of the amygdala (5) versus the simultaneous time (number of steps) and the weighted sum of sensor readings u is shown in Fig.10c. In this figure the intervals marked with the same colour "o" sign correspond to the high frustration level of the amygdala. When u increases, the value of u in which f changes drastically (the threshold) is higher than it is when u decreases. This hysteresis (Fig.10c) is due to the dynamics of the amygdala (5). Therefore, the amygdala remembers for a certain period of time "the fear of encountered obstacles" (or the enhanced puck concentration – for EM2 in Algorithm V). The immune navigator can benefit from the short-term memory of the amygdala in a mixed structure composed of the immune network and the emotional mechanism.

In case of absence of obstacles the artificial amygdala does not influence the action selection mechanism, because $\gamma = 1$ and equation (7) is the same as (2). When obstacles are present the goal following behaviour is switched off ($\gamma = 0$) and the robot focuses attention on the avoidance of obstacles (wall following behaviour or obstacle avoidance). The value $\gamma = -1$ usually corresponds to hard situations when a large obstacle is situated between the robot and the goal. In this case the antibody (from the goal-oriented antibodies), corresponding to the goal direction, has the least probability to win. However, since the detected obstacle is possibly situated in this direction too, the avoidance of the obstacle will be facilitated. Thus in a critical situation the robot forgets about the goal that could cause it to get stuck, and focuses attention on the avoidance of obstacles in order to get out of the impasses. Besides, the emotion mechanism EM1 provides the immune navigator with an additional (small amount of) memory about the obstacles recently met. The navigation becomes more careful, which helps the robot to avoid getting stuck.

Additionally, thirty experiments in three different environments (as shown in Fig.11), were carried out with the mobile robot being equipped with the following navigators: (1) emotionally influenced Braitenberg's architecture No.3c, (2) artificial immune network, and (3) emotionally affected immune network. The structures and parameters of the first navigator were the same as in Refs. (Tsankova, 1999; Tsankova, 2001). In each sample, the robot started from a random initial position and orientation, and had to reach the goal, which was also at a random position. The success ratio of the emotionally affected immune navigator was higher than that of the others (87% vs. 60% (emotionally affected Braitenberg's vehicle No.3c) and 77% (immine navigator without emotional intervention)). At the same time the emotionally affected immune navigator was faster (the average time in steps) about 1.16 and 1.38 times in comparison to the others, respectively (Table 1). The emotionally affected immune navigator had better manoeuvring in narrow passages and Π-shaped obstacles (a very difficult test for the agents with local vision and reactive behaviour, because it often causes an impasse) than the others. Perhaps this is due to the artificial amygdala's property to function as a short-term memory for the fear of encountered obstacles. Besides, the way in which the emotion mechanism EM1 is connected to antibodies reinforces the emerging of wall following behaviour (very useful for overcoming impasses).

The very good performance of the emotionally influenced immune navigator compared with the other two intelligent navigators considered above confirmed the reason to use the emotional intervention for navigation purposes and to transfer it to puck picking up/dropping behaviour control in a stigmergy based foraging task.

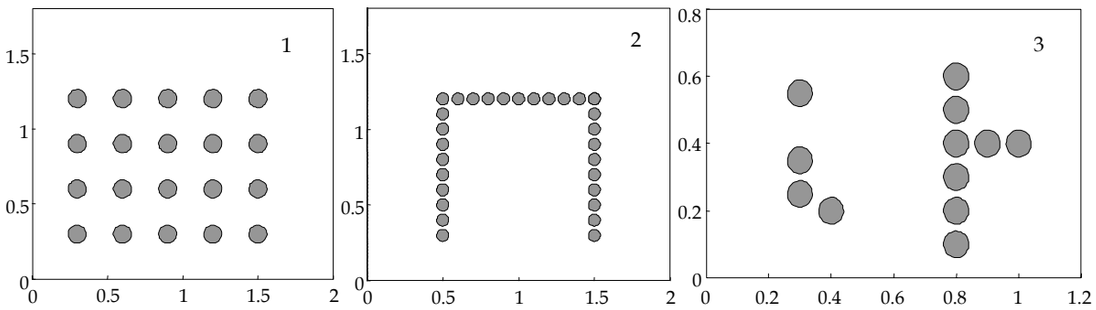


Figure 11. Experimental environments

Emotionally affected Braitenberg No. 3c		Immune network navigator		Emotionally affected immune navigator	
Success [%]	Time [steps]	Success [%]	Time [steps]	Success [%]	Time [steps]
60	2063	77	2460	87	1784

Table 1. Simulation rezults. Each navigator is presented by the average values from thirty experiments, distributed in the environments shown in Fig.11

7.2 Experiments with the five control algorithms

The five control algorithms described above in Section 3 were simulated in MATLAB environment. The use of the first three of them gives a basis for comparison with the last two algorithms, whose purpose is to improve the speed of the puck foraging process. The expectations are that speeding up is to be achieved by: (1) improvement of the collision-free goal folowing behaviour by EM1, and (2) reinforcement of the positive feedback from the

stimuli (minimum/maximum puck concentration) by both EM2 and EM1. The foraging task included gathering pucks in a pile by one robot, working alone, and by two robots working simultaneously.

Simulations of puck gathering behaviour by two robots with the first control algorithm (with random walks) are shown in Fig.12. As Beckers et al. (1994) have specified, the experiments have three more or less distinct phases, regardless of the number of robots. In the beginning there are only single pucks on the arena (Fig.12a). In the first phase, a robot moves forwards scooping one puck into the gripper. When two pucks have been gathered, the robot drops them, leaving them as a cluster of two, and moves off in another direction. Shortly after that most pucks are in small clusters with less probability to be destroyed (Fig.12b). In the second phase, the robot removes one puck from clusters by striking the clusters at a certain angle with the gripper. The puck removed in this way is added to other clusters when the robot collides with them. Some clusters increase rapidly at this phase and after some time there is a small number of relatively large clusters (Fig.12c). The third and most prolonged phase consists of the occasional removal of a puck from one of the large clusters, and the addition of this puck to one of the clusters, often to the one it had been taken from (Fig.12d,e). As a result, a single cluster is formed (Fig.12f). Spatiotemporal structures appear in an initially homogeneous environment, and one of the signs of self-organization is present.

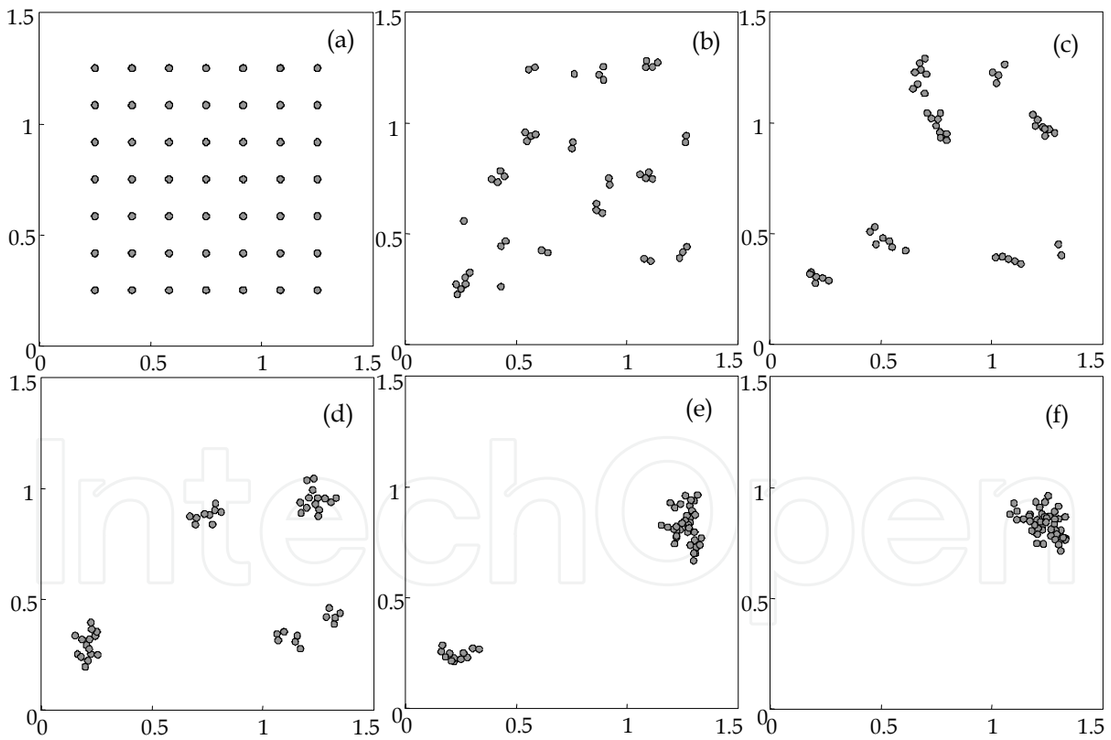


Figure 12. The initial setup (a) and time evolution of a foraging experiment involving two robots. Phase I (b) is characterized by a large number of small clusters consisting of 1 to 6 pucks. In phase II (c) some clusters grow rapidly. Phase III (d, e) includes competition between a small number of large clusters and leads to gathering of all pucks in one pile (f)

The puck dropping mechanism recognizes only a predetermined threshold of puck density – two pucks. It cannot differentiate between the local concentration of two pucks and more than two pucks. Stigmergic mechanism organizes the transfer of pucks from smaller to larger clusters, although the robots under the first control algorithm are unable to discriminate between them with their sensors. The cluster gains pucks from more "frontal" collisions of the robots with it, and loses pucks from almost tangential collisions. The probability for a frontal or tangential collision with a random cluster to be produced depends on the size, shape and position of the cluster. Larger clusters are more likely to gain pucks and less likely to lose pucks than smaller clusters. Due to the constant number of pucks in the environment, in the end all the pucks will be gathered in a single cluster. If the experiment goes on, a puck will occasionally be removed from this single cluster, but it will be returned to it as there is no other pucks in the environment which can trigger the puck dropping behaviour.

In the second control algorithm the random walks are replaced by purposeful moves, taking into account the perceived maximum/minimum concentration of pucks. Under the direction of the place with maximum puck density the robot assumes the direction, corresponding to the sector S_i, whose reading C_i has counted the most of pucks (it makes no difference whether they are situated in one cluster or not). The direction of the place with minimum (non-zero) puck density is determined in a similar way. The robot with an empty gripper goes to the place with minimum (non-zero) concentration of pucks, scooping one puck into the gripper. If there is a puck in the gripper, the robot turns to the place with the maximum pucks and goes forward. The substitution of the random walks with purposeful moves does not violate the stigmergic principles, and only suppresses time-consuming wandering around in an area without pucks. In the third control algorithm the immune navigator implements a collision-free goal following behaviour. The goal directions are the directions with maximum and minimum puck concentrations, depending on the availability or the absence of a puck in the gripper, respectively. However, since the immune network makes decision at the system level, it can assign to the robot a target direction, different from the minimum and maximum puck heaping directions. The innovation in the fourth control algorithm - the emotional intervention (by EM1) on the immune navigator, leads to some improvement of the collision-free goal following behaviour, as it was discused in the previous Subsection 7.1. That includes more successful avoidance of obstacles (the boundary of working area and the other robot) and also tracking the directions of the maximum/minimum puck concentration.

The advisor (EM2) for the puck dropping behaviour is the basic innovation in the fifth control algorithm. In fact advices are followed unconditionally as a permission or prohibition of this behaviour. If the conditions for puck dropping are available, then, in comparisson with the previous algorithms (from I to IV), here EM2 prohibits dropping the puck if its regulation output $\gamma_{\text{puck dropping}}^{\text{prohibit}} = 1$, which can occur when the robot moves from a place with a lower puck concentration to a place with a higher one and the frustration is low (u is under a certain threshold). This prevents the robot from dropping a puck when it encounters a single puck or a small cluster, during motion towards a larger cluster. The robot will drop the retained puck most probably into that large cluster (where $\gamma_{\text{puck dropping}}^{\text{prohibit}} = 0$). However, in the opposite direction, the threshold is lower (because of the hysteresis, which was shown in the example, illustrated in Fig.10c). Therefore, if there is a

puck taken from the large cluster, the robot will drop it in the immediate vicinity of the cluster (in the frame of the frustration's hysteretic zone). That may decrease the probability of destroying the large cluster. The two actions speed up the formation of large clusters. Therefore, EM2 reinforces once again the positive feedback from stimuli, giving the global perception of puck concentration certain superiority to the local one. And the result is present – speeding up the puck foraging process, which is evident from Fig.13, illustrating the time evolution of a foraging experiment involving two robots with the same control algorithm. The parameters of the Amygdala 2 in EM2 were the same as those of the Amygdala 1 (EM1), except for the upper limiting value of frustration, which here was set to be $f_{\max} = 9$.

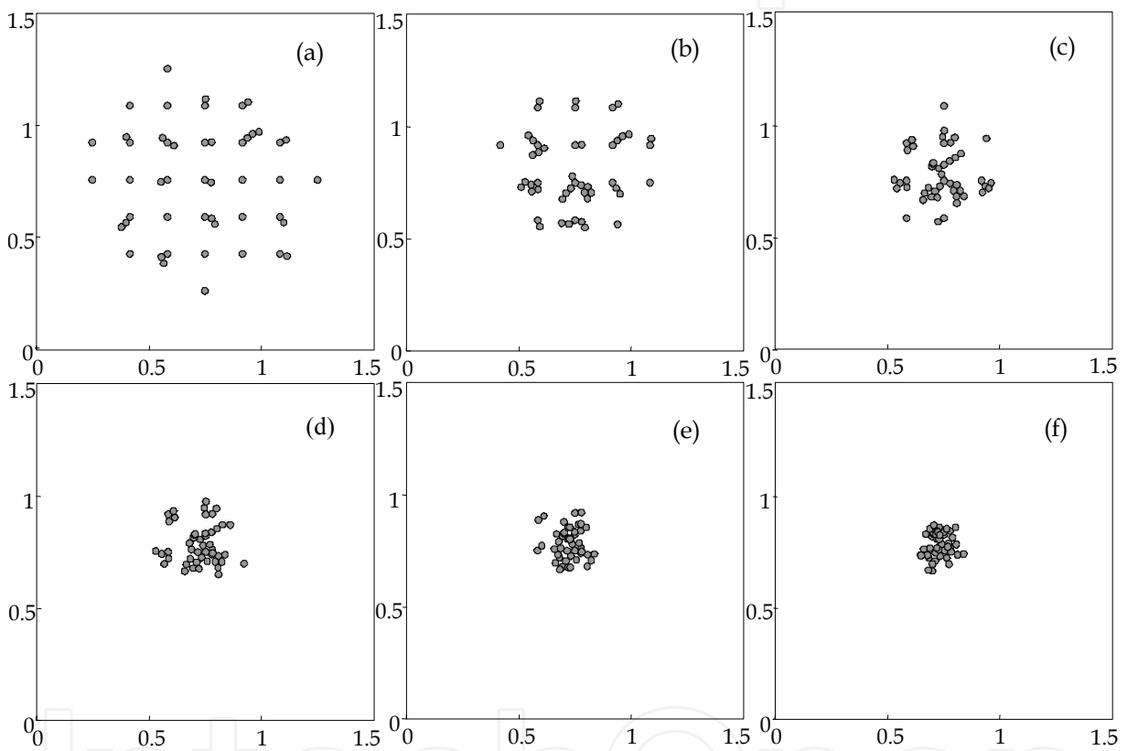


Figure 13. The time evolution of a foraging experiment involving two robots with the two emotional mechanisms EM1 and EM2 (Algorithm V): (a) 1 min, (b) 2 min, (c) 3 min, (d) 4 min, (e) 5 min, and (f) 7 min

Fig.14 illustrates the behaviour of one robot working alone for 1.5 min duration, starting from the initial setup of pucks under a navigation algorithm based on: (a) random walks, and (b) emotionally influenced immune network. The robot with the emotionally influenced immune navigator carried out a specific circular movement, foraging pucks from the periphery to the centre (Fig.14b) and thus forming a central pile (Fig.13f). This effect has been observed in simulations involving a robot equipped only with an immune navigator (Tsankova et al., 2007). Maybe this is due to the *wall following emergent behaviour*, which appears under immune network navigation control and which is reinforced by the EM1.

The simulation experiments with the five control algorithms, involving either one robot working alone, or two robots working simultaneously, led to gathering all pucks in a single pile, located in a random place. The two robots working simultaneously finished the task faster than the solitary one. The average values of (1) the number of clusters and (2) the maximum cluster size from the four experiments with the five control algorithms are shown in Fig.15. The results from these experiments are given in Table 2. The performance of the algorithms is assessed on the basis of the foraging time. The assessment values are the average values of the final foraging time from the four experiments with one solitary working robot and two robots working simultaneously. It is evident that the foraging time decreases drastically from the first to the fifth control algorithm. The achievement of the two robots equipped with the two emotional mechanisms EM1 and EM2 (Algorithm V) and working simultaneously is the best. Unfortunately, the proposed control method, represented by Algorithm V, as the other ones (except for the method, using random walks), relies on a simulated detector for puck concentration, whose physical realization is still an open issue.

Algorithms	Time [min]	
	1 Robot	2 Robots
I. Stigmergy with random walks	1174	705
II. Stigmergy with enhanced sensing of puck concentration	189	109
III. Stigmergy with an immune navigation control	18	13
IV. Stigmergy with an emotionally influenced immune navigation	15	9
V. Stigmergy with two artificial emotion mechanisms	10	7

Table 2. Performance of the five control algorithms, described in Section 3. The foraging time is presented by the average value from four experiments

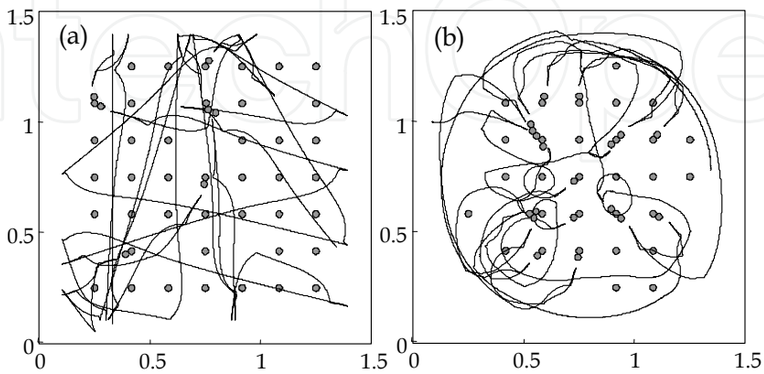


Figure 14. Simulation of a foraging behaviour of one robot working alone for 1.5 min duration, starting from the initial setup of pucks under navigation algorithm using: (a) random walks, and (b) emotionally influenced immune navigator

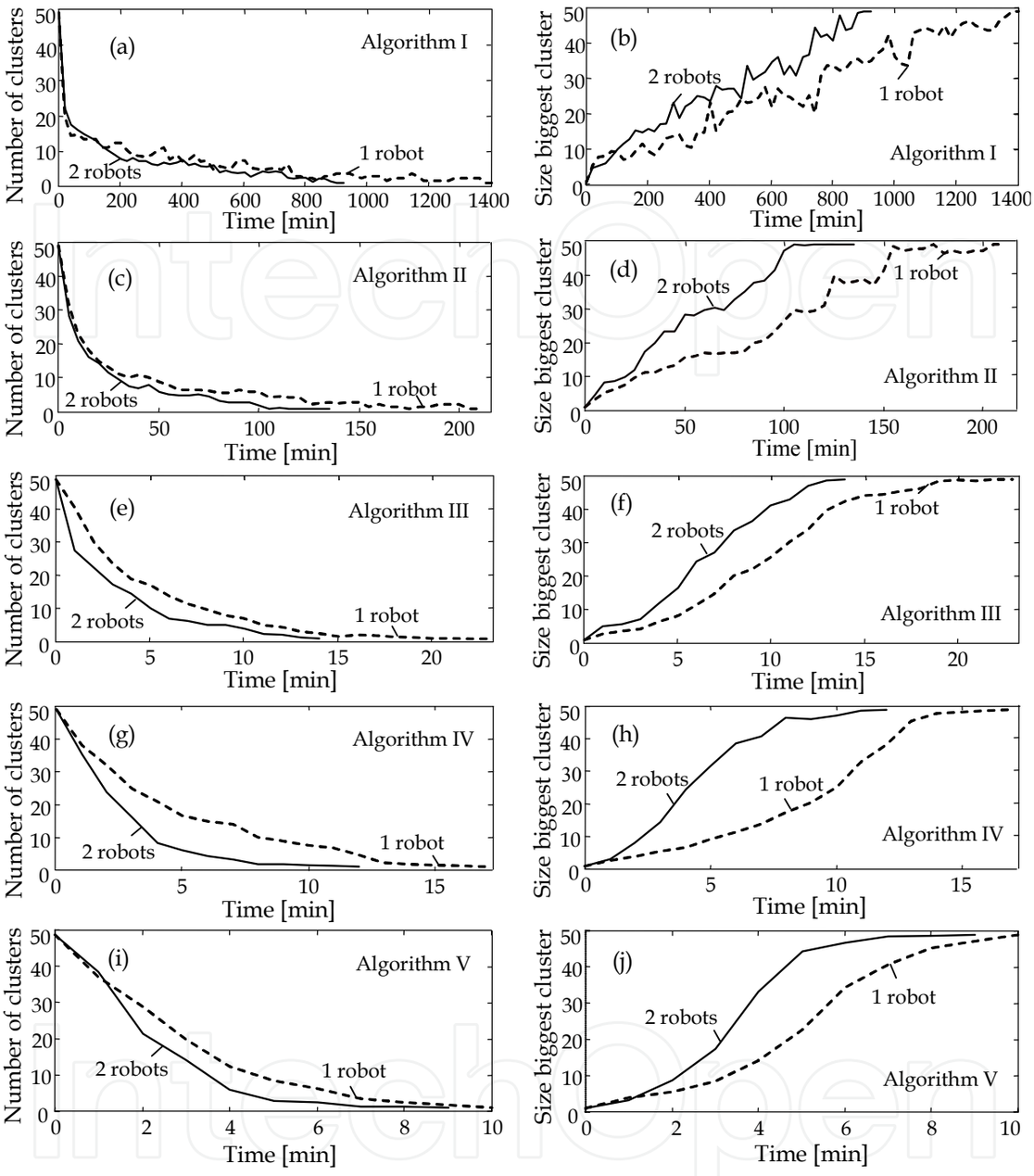


Figure 15. Time evolution of the number of clusters and the size of the biggest cluster for experiments with the five algorithms

8. Conclusion

The proposed stigmergy based foraging behaviour control using two artificial emotion mechanisms – one as a superstructure over the immune navigator, and another as an advisor of puck picking up/dropping behaviour, improves the speed of the clustering process. The intervention of the EM1 on the immune navigator improves the collision-free goal following behaviour of each robot, which affects the final implementation of the

foraging task. Besides, it enhances the positive feedback from the stimuli, since it improves the tracking of the direction of sensor reading for the minimum/maximum puck concentration. The intervention of the EM2 on the puck dropping behaviour reinforces once more the positive feedback from the places with maximum puck concentration. Future work will include the use of optimization techniques for parameter tuning of the amygdala model of the emotional mechanisms EM1 and EM2, as well as of the immune network. It is also necessary to experiment with the proposed emotionally influenced control on real immune network driven robots implementing a puck foraging task. This brings up the question of the physical realization of a detector, resembling the simulated sensor for puck concentration.

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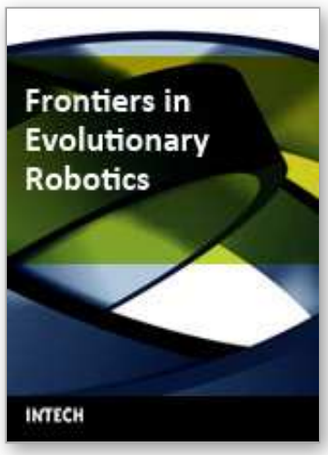
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This book presented techniques and experimental results which have been pursued for the purpose of evolutionary robotics. Evolutionary robotics is a new method for the automatic creation of autonomous robots. When executing tasks by autonomous robots, we can make the robot learn what to do so as to complete the task from interactions with its environment, but not manually pre-program for all situations. Many researchers have been studying the techniques for evolutionary robotics by using Evolutionary Computation (EC), such as Genetic Algorithms (GA) or Genetic Programming (GP). Their goal is to clarify the applicability of the evolutionary approach to the real-robot learning, especially, in view of the adaptive robot behavior as well as the robustness to noisy and dynamic environments. For this purpose, authors in this book explain a variety of real robots in different fields. For instance, in a multi-robot system, several robots simultaneously work to achieve a common goal via interaction; their behaviors can only emerge as a result of evolution and interaction. How to learn such behaviors is a central issue of Distributed Artificial Intelligence (DAI), which has recently attracted much attention. This book addresses the issue in the context of a multi-robot system, in which multiple robots are evolved using EC to solve a cooperative task. Since directly using EC to generate a program of complex behaviors is often very difficult, a number of extensions to basic EC are proposed in this book so as to solve these control problems of the robot.

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