First Investigations into Artificial Emotions in Cognitive Robotics

Daniel Moser[1], Ronald Thenius[1] and Thomas Schmickl[1]

Abstract In nature, the combination of processes of emotion and cognition has a deep impact on type and quality of reaction to environmental stimuli. In this work, we want to test the feasibility of artificial hormones in artificial neural networks. We take a minimal evolving neural network and look into the implications and opportunities of extending this model of communicating nodes, with one virtual hormone gland. To explore the differences in behavior, that we expect to develop with this modification, we modify an already well established model, the Braitenberg Vehicle. These vehicles were faced with a simple energy gathering task. The behavior, efficiency and fitness of these vehicles in identical environment, with the artificial hormone active and inactive, is examined. It shows, that the implementation of artificial emotion leads to an increase in efficiency of the evolved solution.

Key words: artificial emotions, neural networks, complex behaviors, artificial evolution

1 Introduction

1.1 Motivation

To navigate in, and react to an immensely diverse and dynamically changing environment, is a challenging task for robots. As the challenges of mechanical nature in the field of robotics were often conquered with bio-inspired solutions, it is logical to look in the same direction when approaching cognitive problems.
Humans and other animals are quite versatile in these kind of tasks, so we propose to explore methods to implement bio-inspired approaches in artificial systems to

[1]Artificial Life Laboratory, University of Graz, Austria
Corresponding author: daniel.moser@uni-graz.at

close this gap. Further, it is paramount for agents in these environments, to fully function with the lowest possible expenditure of available energy, so efficiency is a key factor of success. This is true for power consumption as well as navigation and task fulfillment. The notion that cognition and emotion are closely linked is already well documented [21]. It is also suggested that experimental cognitive and emotional robotics can provide insights into emotion theory and neuroscience [4]. In this paper we define artificial emotion as a feedback-loop in the interconnected system of neurons, gland and artificial hormone. This self influencing cycle has simplified characteristics of the above mentioned natural systems, and as such is an bio-inspired extension to the already bio-inspired Artificial Neural Network (ANN), which is shortly described in Section 2.1.

What we expect to get from the exploration of this subject in the long run, is :

- A novel approach to cognitive adaptability and context dependent decision finding in agents.
- An increase in efficiency in the use of computing resources and in energy management.

1.2 The questions

To start our investigation regarding the feasibility of implementing an artificial hormonal, we formulated three questions:

1. *Question Q.1* Can the efficiency of an artificial neural network be enhanced by a self-influencing, system-wide simulated neuromodulation with artificial hormones?
2. *Question Q.2* What increase in efficiency can we observe and possibly exploit for cognitive robotics?
3. *Question Q.3* Does evolution use and hold the features of artificial emotion?

1.3 The hypothesis

Based on the above mentioned question $Q.1$ we formulated following hypothesis:

H0 : The implementation of a hormonal system has no influence on the performance of an ANN.
H1 : The implementation of a hormonal system has some influence on the performance of an ANN.
H1.a : The implementation of a hormonal system decreases the performance of an ANN for the tested task.
H1.b : The implementation of a hormonal system increases the performance of an ANN for the tested task.

Due to the fact that question $Q.2$ aims for the implementation in the context of a real-world robotic system, we decided to use descriptive formulations to answer this question, instead of formulating a hypothesis.

2 The method

To test the above mentioned hypothesis and questions, we developed a simple multi-agent simulation, including artificial evolution. Inspired by previous work about artificial emotions and neuromodulation in ANNs [19], an experimental setup was chosen to test our hypothesis. Multiple agents, equipped with a simple neural-network, had to collect food and reproduced, given the reproduction threshold R was reached (see Table 1). The developed simulation environment was designed for fast testing of the hypothesis, and a minimum of parameters. This allowed for having a maximum of generality for the acquired insights into evolving ANNs and the influence of artificial emotion systems. The programming environment we chose was the NetLogo 5.3 simulation and modeling environment [20]. A more detailed description of the simulation processes, procedures and the simulation interface can be found in Section 2.2.

2.1 The Artificial Neural Network

Artificial Neural Networks are inspired by the biological brain and are in stark contrast to the functionality of the standart von Neumann model of modern computing machines [9]. First investigations have been published as early as 1943 [11] and renewed interest emerged with the advances in the developement of back-propagation learning algorithms in 1986 [13] and with advances in hardware, that made it possible to create more complex and complete models.
An ANN constists of a network of interconnected mathematical entities called neurons.
Each neuron calculates a sum of its weighted inputs. The weight on each input can be either inhibitory or excitatory and therefore influences the result of the calculation and the output of the neuron.
This setup allows for adaption and the ability to *learn*. In the context of ANNs, learning describes the reforming of connections and updating of the input-weights in each neuron to fit the task. An ANN can be trained with predefined examples of correct results to a specific task, without an explicitly given set of rules.
The calculations that happen in the neurons itself in combination with the topology of the network is of great importance for the functionality and many approaches and techniques have been proposed [18],[16] for different systems.
The network used in this experiment, exhibits all traits of an ANN. As Figure 3 shows, the two Synapses and the Hormone Gland of the agents are a simple net-

work of neurons with multiple connections.

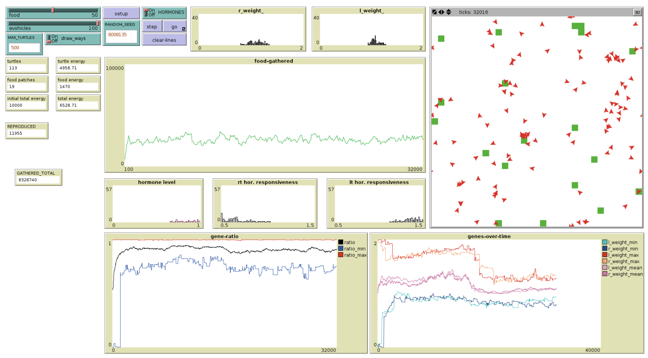

Fig. 1: Interface of the simulation environment developed to test how an artificial hormone system influences the efficiency of an ANN.

2.2 Structure of the simulation

The setup for the conducted experiments in this simulation consisted of empty ground-patches and randomly scattered food-source-patches that initially contain E energy-points (see Table 1). An example of such a randomly generated world can be seen in Figure 2. The amount of food-source-patches was set to a fixed value P. Values of P and other constants used in the presented experiments can be found in Table 1. The spawning agents were set to a fixed value B (see Table 1). The agents were then randomly placed on coordinates, which were not food-sources or already occupied by agents. The food-source patches regrowed on a random position if consumed, the detailed mechanics of this process are described in Section 2.6.2.

Besides the energy decreasing measure when reproducing, other inhibitory procedures against unregulated growth were set in place. The initial energy in the system, consisting of the energy-points abundant in food-resource-patches and agent-energy was logged and stored in a global variable.

Each time the *regrow* procedure was called, the total-energy in the system was calculated and only if the addition of another food-source would not have exceeded the initial total-energy, the food-source was created.

Further, the same calculation was done each time the *reproduction* procedure was called and if the limit was reached, the agents got capped at the reproduction-threshold until the system had leveled out again.

The authors are fully aware that this is an inaccurate depiction of energy flow in natural systems, but an adequate approximation, that fulfills the requirements to test the hypothesis mentioned in Section 1.3.

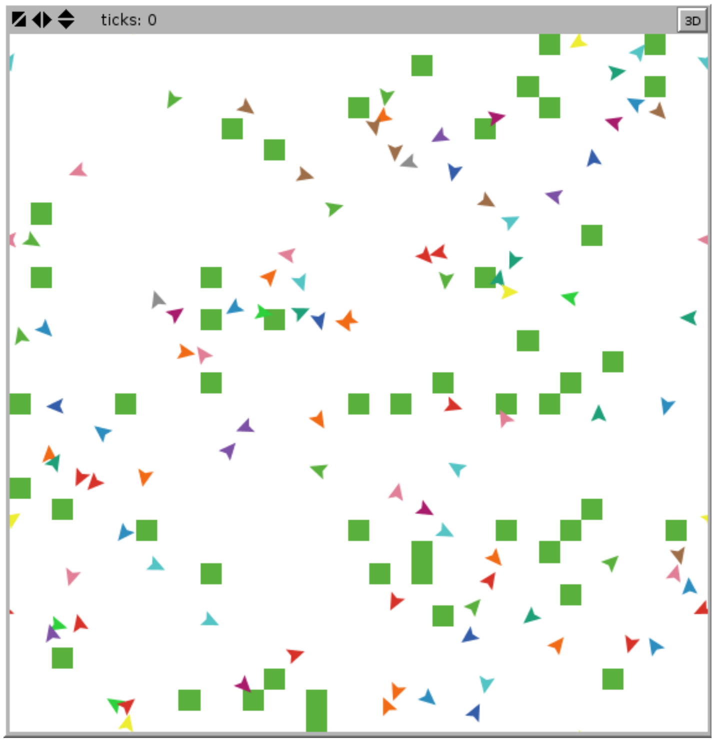

Fig. 2: The simulated world directly after setup and zero time-steps. The triangles represent the agents which can move around. The green squares are stationary food-source-patches.

2.3 The agents

In their basic abilities, all the agents were identical. They can sense food-sources, accelerate forward, decelerate, rotate on the spot, eat, reproduce and die. The quality of the sensory, eating and reproducing abilities was also identical in every agent, and described in detail in Table 1.

Variable	Explanation	Value	Unit	Constant	Evolving	Scope
A	Age	0	Time-steps	No	No	Agent
B	Agents in the simulation	100	Agents	Yes	No	Global
C	Energy after reproduction	40	Energy	Yes	No	Global
E	Initial energy on food-patches	100	Energy	No	No	Global
F	Food gathered	0	Energy	No	No	Global
H	Initial hormone level	0.3	-	Yes	No	Agent
M	Max energy gathered per time-step	10	Energy	Yes	No	Global
P	Food-source-patches in the simulation	50	Patches	Yes	No	Global
R	Reproduction threshold	100	Energy	Yes	No	Global
S	Max speed of agents	2	Patches	Yes	No	Global
U	Mutation factor	0.05	-	Yes	No	Global
w_1, w_2	Dampening or amplifying factor	0...1	-	No	Yes	Agent

Table 1: This table describes the constants and variables used in this paper in the context of the simulation environment.

2.4 The tested networks

Figure 3 shows the schematics of an agent with the two sensors that were connected to the opposite motors through the weighted synapses. The hormone gland got activity signals from the right sensor. This influenced the outcome of the hormone-level calculation in Equation 1 which in turn influenced on the calculation in the synapses as shown in Figure 2.

2.4.1 The Braitenberg vehicle

The agents were a simple ANN-controled Braitenberg vehicles of type 2*b* [3]. They had two wheels, actuators and motors on opposing sides that can be controlled independently. For further simplification of the navigation process, the movement was limited to forward and the maximum speed was set to S (see Table 1). By controlling the difference in speed of each motor, the direction and speed can be adjusted. In our design, the wheels were placed at a distance of two patches. The two sensors were placed on the axis of the wheels in a distance of one patch from each other, and connected to the opposite motor. At the start of each experiment these two connections, w_1, w_2 (see Table 1), were weighted. Evolving w_1 and w_2 (as described in the Section 3.1) lead to effective controllers emerging during the experiment run.

2.4.2 How did we implement emotion

Contrasting to several experiments that have been conducted as to how artificial emotion or cognitive functionality could be implemented into ANNs [8][19][10], a novel approach was devised in this work. We diminished complexity to an absolute

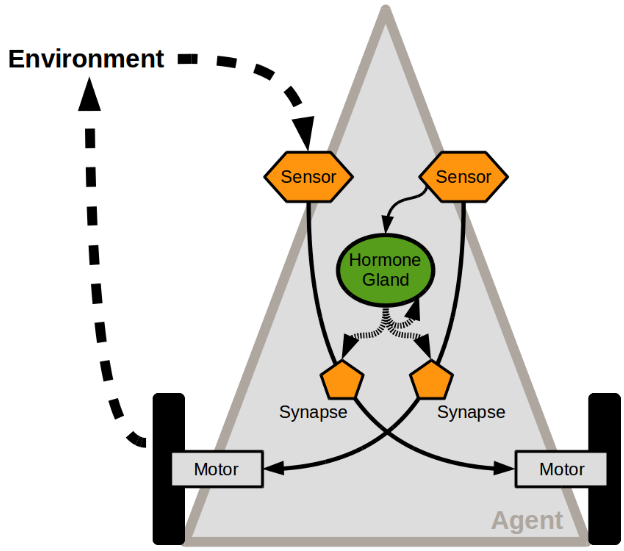

Fig. 3: A depiction of a Braitenberg vehicle of type 2b, extended with 2 synapses and a hormone gland. In the simulation the gland can be activted or deactivated.

minimum, to reach general. but clear results. To implement the described functionality, we added a virtual gland to one of the sensors. Depending on the input of this single sensor, the level of one type of artificial hormone in the system is regulated. This process is shown in Equation 1.

The initial value of the artificial hormone level at the beginning of each experiment was set to H (see Table 1). The level in the current time-step was influenced by the level in past time-step, allowing for prolonged effects of intense-input events and therefore a self influencing loop.

$$h_{level} = h_{level} \cdot 0.9 + sensor_{input} \cdot 0.1 \tag{1}$$

Whereby h_{level} represents the current level of hormones in the system and $sensor_{input}$ represents the input from the connected sensor to the gland.

Each weight in itself is weighted by an evolving hormone-receptivity, that influences the input-output conversion as shown in Equation 2.

$$sensor_{input} = sensor_{input} \cdot (responsiveness_{h,weight} \cdot h_{level}) \tag{2}$$

Whereby $sensor_{input}$ represents the input from the respective sensor, $responsiveness_{h,weight}$ represents the responsiveness of the respective weight to the hormone level h_{level} in the system.

All experiments were conducted with hormone glands active, as well as with inactive glands. This allowed for direct comparison of efficiency and fitness of the agents in the two configurations.

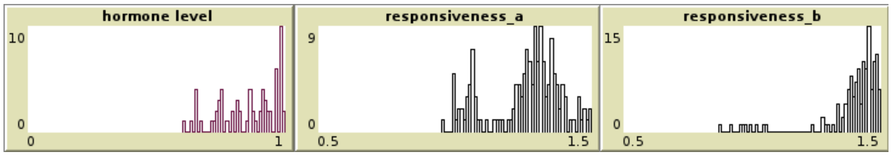

Fig. 4: The hormone levels in the agents and the respective receptivity weights in a population of 77 agents. The hormonal functionality was activated and $10,000$ time-steps of a randomly chosen run had passed. The x-axis represents the different genes that influence the hormone level and responsiveness of the weights to these hormones. The y-axis represents the distribution of these genes in the population. This shows, that the hormone system had also a functioning evolutionary process, as the genes accumulated and were not distributed evenly across the spectrum.

2.5 *Evolution*

On-board evolution in swarm robotics has proven to be effective in simulation as well as in real world applications [2][15]. For this experiment, we chose a simple, two-weight system. The initial values for the weights were chosen as a random generated float between 0 and 2, and then applied to the sensory input signal as described in Equation 3. These values were chosen after testing boundaries, and seemed feasible to the authors, since the behaviour of the evolutionary process is not influenced.

$$actuator_{output} = \frac{(weight \cdot sensor_{input})}{MS} \tag{3}$$

Whereby $actuator_{output}$ represents the signals that were sent to the motor by the controller, *weight* represents the dampening or amplifying factor between sensor and actuator and S represents the maximal speed of an agent (see Table 1). The weights can therefore amplify or dampen the intensity of the communication between sensors and actuators. Was the random configuration of an agent advantageous in finding the food-resources, this agent was likely to reach the reporduction-threshold R (see Table 1) and hatch another agent with a mutated but similar genetic material. The details of the mutation process are described in Section 2.5.2.

2.5.1 Reproduction

As the agents evolved to navigate to food-sources and consume them, their energy-points exceeded the reproduction-threshold of R (see Table 1). As soon as this happens the *reproduction* procedure is called.
The procedure resets the energy-points of the reproducing agent to C and spawns an agent on the same patch. The reduction of energy represents the loss of energy due to the reproductive process. The hatched agent receives C initial energy-points.

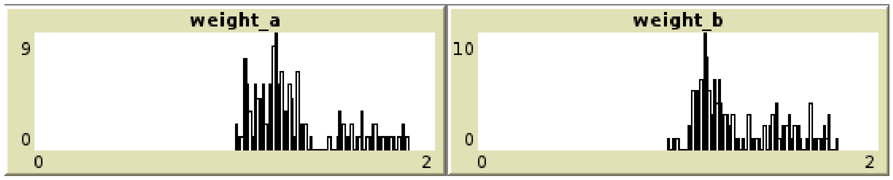

Fig. 5: The distribution of the evolved weights in the agent-set, after 10,000 time-steps in a randomly chosen run, and with hormonal effects activated. The x-axis represents the different genes that influence the factor that translates the sensory input signals to the actuators. The y-axis represents the distribution of these genes in the population. This shows an emerging evolutionary pattern in the controllers, as genes accumulate around advantagous values and are not evenly distributed.

The *mutate* procedure is called, slightly changing the w_1 and w_2 of the controller. A detailed description of the mutation process can be found in Section 2.5.2.

2.5.2 Mutation

The mutation process applies to the weight parameters of the agents.

- $weight\_a, weight\_b$:
  Applied to the respective sensory input of the agent, this weight either amplifies or dampens the input signal that gets communicated to the opposite motor-actuator.
- $responsivity\_a, responsivity\_b$:
  If the hormone system is activated, these weights determine the rate of reaction of the above mentioned weights to the systems hormone level.

Every one of these parameters was randomly mutated by increasing or decreasing the float-value associated with it. The amount of mutation is determined by a random float between 0 and U (see Table 1), that was applied to each of the weights, as shown in Equation 4.

$$weight = weight \pm rand(U) \tag{4}$$

Whereby *weight* represents the dampening or amplifying factor between sensor and actuator, $rand(U)$ represents a random float number between 0 and U (see Table 1). The results are limited inbetween 0 and 2 for the input weights, based on the chosen values described in Section 2.5. The limits for the hormone responsiveness weights were chosen between 0.5 and 1.5. The authors tested several ranges of responsiveness and concluded based on the simplicity of the model and the observed behaviour on these values.

The authors are fully aware that this is a very string simplification of the process of nature. We want to point out, that the process of mutation is simulated in such a way, that makes it possible to test the hypothesis mentioned in Section 1.3.

2.6 The experiment

2.6.1 Overview

To test the hypothesis mentioned in Section 1.3, we ran several simulation experiments, as described in Section 2. One experiment run lasted for $10,000$ time-steps. This value was chosen arbitrary after observing several runs and concluding the system has stabilised at this point. Each experiment was repeated twenty times. We measured how many energy-points were collected, and how much energy was invested into movement to collect energy-points.
The efficiency e of the population was calculated based on the collected energy c of all agents and the expended energy o of all agents, according to the Equation 5.

$$e = o/c \tag{5}$$

Whereby e represents an efficiency value, o the expended energy and c the gathered energy.
One set of experiments was done with classical Braitenberg vehicles, without a hormonal system included. A second set was performed including a hormonal system. The ability of the described system to evolve controllers, that were able to collect more energy than they consume was observed, as well as the efficiency e of agents with and without hormones.

2.6.2 The task

Agents were confronted with the task to survive by finding and consuming food, that was randomly scattered in the world. The goal of each agent was to reach the reproduction-threshold of R (see Table 1) that lead to hatching offspring that carried similar genetic material that was defined by the weights, e.g. genes, in each system. This procedure is detailed in the Sections 2.5.1 and 2.5.2.

In the given task more speed meant getting to food-sources faster, but also costed more energy. As more food can be consumed the longer the agent was in direct contact on a food-source, an optimal solution of dynamic movement had to be found. The fixed abundance of food was a challenge to the competing agents, as faster movement got the individual agent to the food-sources quicker, but also minimized the amount of food that can be consumed from the patch if the deceleration was not adequate. The evolved weights of successful agents were kept in the population pool and were amplified through asexual reproduction. Per default every food-source-patch spawned with E consumable energy-points on it, and every time-step an agent resided on one of these patches, this agent received M (see Table 1) energy-points. When the food-source was depleted, the regrow-food procedure is called. To not exceed the initial energy of the system, this function calculated the total energy in the system, and if another food-source would not have exceeded the initial energy, it created a randomly placed food-source on an empty patch .

3 Results

3.1 Evolutionary process

Our system showed the evolution and persistence of successful traits as seen in Figure 5. Both types of agents (with and without hormones) were able to evolve controllers, that were able to collect energy and “reproduce” in the simulated environment, as described above. Further the adaptation of the agents within the evolutionary process was observed. An exemplary result for the adaptation of the genes over time can be found in Figure 6.

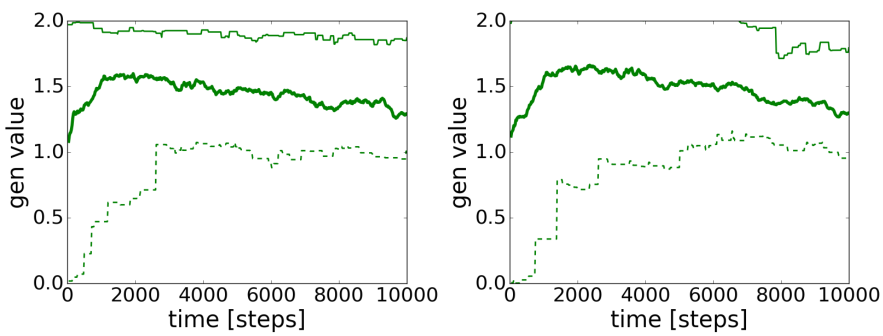

Fig. 6: Graphs of the maximum, minimum and mean values of the two weights over time, with hormonal functionality activated and after $10,000$ time-steps. Whereby the solid thick line represents the mean of the maxima/minima of the two weights, the dashed line represents the maximum/minimum of the right weight, and the solid thin line represents the maximum/minimum of the left weight.

3.2 Comparison of efficiency

The comparison of the efficiency, as described in Equation 5, showed, that agents evolved with a hormonal system had a higher performance for the given task as seen in Figure 7. After $10,000$ time-steps the agents with a hormonal system had evolved a controller that is significantly more efficient then agents without an hormonal system.

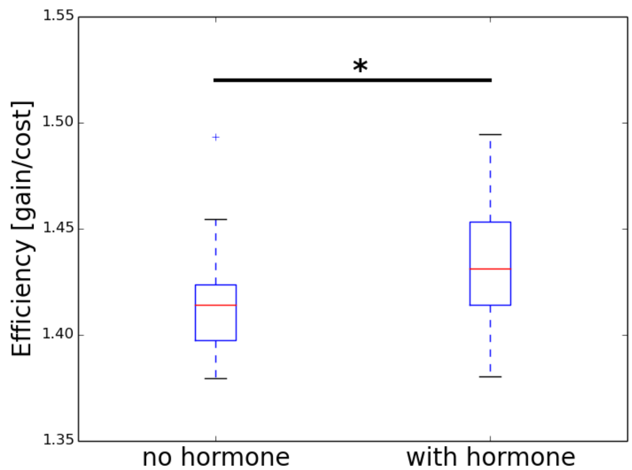

Fig. 7: Comparrison of the efficiency e of neural networks with and without hormonal modulation. It shows that the system with hormonal modulation has a significant higher efficiency. $N = 20$, *: p $\leq$ 0.05, MannWhitneyWilcoxon-Test.

4 Discussion

4.1 General outcome

With this work, we show that hormonal feedbacks have an influence on the ability of an artificial neural network to evolve an efficient controller for the given task described in Section 2.6.2. Both types of controllers (with and without hormones) were able to reproduce in the given environment, and, on a genetic level, adapted to the the given environment. Regarding the hypothesis presented in Section 1.3, it can be said, that $H0$ and $H1.a$ could be rejected. We could not reject Hypothesis $H1.b$ (including $H1$). Regarding the questions formulated in Section 1.2 we can conclude:

1. *Question Q.1* **Yes,** artificial neural networks efficiency can be enhanced by simulated neuromodulation with artificial hormones?
2. *Question Q.2* The implementation of a hormonal system significantly **increases** the efficiency for the given task, as seen in Figure 7.
3. *Question Q.3* **Yes,** In all tested runs evolution found solutions that included the artificial emotions.

4.2 Limitations of the presented results

The results presented here are based on first experiments in an extremely simple environment, with a minimalistic neuronal controller, and a minimalistic hormonal controller. This design was necessary to test basic features of the system from a very general point of view. The authors are aware, that, although the insights into the described system are very general, the implementation into a more detailed simulation environment and into actual robots itself has to be done to fully support this claim. The interplay of neural networks and virtual hormone systems could be advantageous in complex and dynamic physical environments in the real world, given an appropriat complexity for the given task.

4.3 Comparison with literature

As mentioned in the introduction, the inspiration for the theory behind this experimental approach, resulted from the study of some general work on artificial intelligence and emotion [1][6][7]. Research into the less artificial neurological aspects proved to be valuable and inspired the theory behind our approach [14][5]. Especially the work by Fellous and Arbib on emotions from a purely functional viewpoint, seeing emotions not as emotional expression for communication and social coordination, inspired us to this approach. Prooving the feasibility of using emotions as a functional "tool" for organizing behavior, action, reaction and learning in an evolving system, has been tried before. But given the complexity of these processes in nature, simulations seem to have gotten rather complex as well. In contrast to this, an opposite approach was chosen in this work. The idea was to model the most simplified simulation environment, that allowed to conduct experiments on the impact of artificial emotions on a neuronal network. In [8] a very complex system with a distinctive seperation of sensations, feelings, emotions and hormones is proposed. This model has also some key functionality that we wanted for our work; The reaction to not only current sensory input, but an output that is strongly influenced by past sonsory or emotional events. The setup of the networks was rather complex as well, as a distinction between feelings and emotions was made. The authors of this work concluded, that the suggested artificial emotion modifications of their systems proved to have a slight improving impact on the systems performance.

Extensive research on the topic neuromodulation in artificial systems has been conducted in a master-thesis by Lo [10], with a focus on implementation on different kind of ANNs and in an environment of T-maze navigation tasks. In contrast to these we wanted to implement a comparatively more realistic task than the former example, a simulation with more than one agent and theoretically indefinite runtime. We also wanted to reduce the complexity of the simulated emotions to reduce error and result-complexity.
This chosen approach allowed us the possibility to quickly estimate the real-world value of our findings.

5 Future work

The work presented here is the first step on a research track investigating the usability of self-modulated artificial neural networks in robotics, as well as a tool in cognitive robotics in general. This system will be tested on both, actual robots and extensive simulations for feasibility. A challenge lies in the transfer of a neural network, that is in the state of adaptation from one robot to another, while deployed in various tasks. Major focus will be laid on underwater service robotics [17][15][12] and the usage of the presented adaptive system in highly dynamic underwater environments in interaction with eachother, the surrounding ecosystem and humans.

6 Conclusion

Summing up the results presented in this work, we conclude that the combination of hormonal and neuronal controller structures lead to a change of the dynamics in the described system. We plan to exploit this feature for robotic systems and their application. Especially the increase of movement dynamic based on the hormonal influence will be investigated in detail. To which extent these concepts of artificial evolution and emotion are directly applicable in scientific or technological scenarios is topic of ongoing discussions and investigations.

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