

# TYPES OF ANTICIPATORY BEHAVING AGENTS IN ARTIFICIAL LIFE

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## ABSTRACT

Anticipation is broad multidisciplinary topic but there are little thoughts on its relation with the reactive behaviour, the similarities and where the boundary is. Reactive behaviour is still considered as the exact opposite for the anticipatory one. It was shown that reactive and anticipatory behaviour can be combined. We will present own viewpoint. Our multi-level anticipatory behaviour approach is based on the current understanding of anticipation from both the artificial intelligence and the biology point of view. The terms as weak and strong artificial life will be discussed here. Original thought is that we use not one but multiple levels of anticipation in a creature design. We focus on the first 2 levels within the 8-factor anticipation framework here. These first two levels may seem trivial, but growing interest in implicit anticipation and reactive anticipation suggest that this is a worthwhile topic. The simplicity of them is intentional to demonstrate our way of thinking and understanding of the topic. The comparison with other results is possible only when these levels are integrated into the complex architecture that can also act as standalone. Examples of experiments follow.

## INTRODUCTION AND STATE OF THE ART

The field of Artificial Life (ALife) simulators is very diverse. Most of freely available simulators are concerned with only one phenomenon of ALife.

All beings of nature use anticipation whether they are aware of it or not. Our approach is to our knowledge one of the first that looks at the conscious and unconscious part of anticipation separately. What is not so obvious, that anticipation is not matter of a single mechanism or a control block in a living organism. Anticipation happens on many different levels even in very simple creatures. The works studying anticipation in the past overlooked this fact, focusing on the anticipatory principle or mechanism only. And that exactly allowed us to use not one, but several levels of anticipation in a creature design and to observe the results.

There were two motivational examples to us:

The first example is taken from work (Nadin 2003). Change in posture (standing up from a seated position for example) would cause changes in blood pressure. This is the physics of the body consisting from a liquid (blood), pipes (the various blood vessels), and a pump (the heart). We can understand the mechanism by taking a rubber tube with liquid inside and manipulating it. The pressure of the fluid varies as we change its position from horizontal to vertical according the physical laws. If human beings were subjected to such blood pressure variations as often as we change posture, we all would have a terrible time. So what did we miss? It appears that a certain reflex, called the baroreceptor reflex, affects the heart rate via the nervous system in order to maintain the blood pressure within relatively constant and safe limits. But how does the heart “know” about a change in position? Obviously, the analogy to the simple physical system of a machine with liquid pipes and pumps ends here. The question asked “how does the heart, or whatever controls the heart, know what the body will do” goes beyond the physics of pumping a liquid through pipes. Please note here that this process is not consciously controlled.

As another example showing different level of anticipation, to explain our postulate above about different levels, we can use something very common a tennis player. While playing the opponent, a player is trying to estimate (based on measured observations) the opponent’s action and also the result of his action (which is a trajectory of the ball). This estimate is based on the “model” the player has. This model contains among other things the human body physiology, the laws of gravity and physics. These are not expressed as equations but as patterns and rules for reaction. These patterns and responses can be improved by training.

It may seem that these two examples bear little resemblance of them, however they have something in common. In both the *prediction of future state* plays important role in closing the loop of regulation (control) namely. The prediction influences the decision about current state anticipation and the behaviour influenced by the future state anticipatory behaviour. This clearly suggests that anticipation is not just another function of the organism; it is *built in* and applied *on different levels*.

Our goal is to implement anticipation in the agent architecture. While analysing the state-of-the-art, we have felt a gap in the theories shown on the previous example. So initially we focused on revision of the

current theories and in the end we tried to formulate own theory. We have received a proof that anticipation, implemented even on these multiple levels can be beneficial with much better results. For this as mentioned, it is necessary to integrate at least the 6 out of our 8 levels in an architecture that can be compared to the other works. Even though our research is not directly tight to an industrial application so far, the anticipation can be applied in variety of areas, because it goes beyond the future state estimation. It provides this as an additional *input* to decision or regulation mechanism. Primary industrial application of our approach is intelligent robotics and humanoids.

## **WEAK AND STRONG ARTIFICIAL INTELLIGENCE, LIFE AND ANTICIPATION**

Before we start describing our view on the reactive and anticipatory behaviour in artificial creatures, we are to discuss the differences between weak and strong approaches in area of *Artificial Intelligence* (AI), *Artificial Life* (ALife) and *Anticipation*. The fundamental difference between strong and weak approach is that in *strong systems* we try to have the required feature while in the *weak systems* we focus “only” on appearing that the system has the required features. Both approaches are valid and have their pros and cons and also their representatives.

### **Weak and Strong Artificial Intelligence**

We can say that strong AI tries to think (act) like humans, while the weak AI tries to think “intelligently” (approximation of human thinking). Reaching the strong AI is hard and it is subject of many arguments and debates. The classical artificial intelligence is focused on the process of thinking, reasoning, problem solving and planning. These problems are usually addressed separately. On the other hand the modern approaches are focused more around behaviour. To this category fall even ALife and the anticipatory behaviour research. Please note that anticipation as such is a general principle and does not fall in the ALife category while the anticipatory behaviour does!

### **Weak and Strong Anticipation**

In view of explicitly mathematically defining systems with anticipation, Dubois introduced the *concept of incursion, an inclusive or implicit recursion*. An incursive system is a recursive system that takes into account future states for evolving. Some non-linear incursive systems show several potential future states, what are called hyper-incursion. A hyper-incursive anticipatory system generates multiple potential states at each time step and corresponds to one-to-many relations. An endo-anticipation is an anticipation built by a system or embedded in a system about its own behaviour. This is no more a predictive anticipation but a built anticipation. In this case, this is a *strong anticipation*. An ego-anticipation is an anticipation made by a system about external systems. In this case,

anticipation is much more related to predictions or expectations. This defines a *weak anticipation*. The anticipation of a system can be based on itself, rather than its environment. In a summary the *strong anticipation* refers to an anticipation of events built by, or embedded in a system, *weak anticipation* refers to an anticipation of events predicted or forecasted from a model of a system. We can see that the AI and anticipation understanding are a bit different. Since ALife is part of Artificial Intelligence studies and also employs anticipation, we need to clarify the differences. We identified 8 factors of anticipation in our new approach.

### **Weak and Strong Artificial Life**

Now we would like to put what was said so far into the context of our ALife domain. From AI point of view the ALife belongs to the weak AI category because it is mostly satisfied with approximating rational behaviour and sometimes (especially in life-as-it-could-be simulations) not even that. It seems that the terms of strong and weak properties are different in AI and anticipation fields. Since our primary field is the ALife with anticipatory behaviour we need to be aware of both aspects. What is understood under a strong and a weak ALife? How the weak and strong anticipation are projected in the weak and strong ALife? Since ALife was historically derived from the AI, it also uses the AI understanding of strong and weak property. Weak ALife is viewed as an attempt to learn more about biological life by creating synthetic models of various processes associated with living organisms (e.g. evolution) on artificial media, but do not claim that any parts of their models are actually living themselves. Strong ALife claim that by instantiating such processes in artificial media, the end product will be just as deserving of the term “living” as are biological organisms. Since the artificial creatures created in ALife domain are usually situated in open environment, from the point of anticipation definition they need to employ both weak (*exo*) anticipation and strong (*endo*) anticipation (Elmahalawy and Nahodil 2007a).

From the ALife point of view, the *strong anticipation* is about deriving *information about future without a model* (the only model available is the creature itself). We can easily imagine that if the creature would be complex enough it could model even the situations in the environment on self. The creature in weak understanding has the capability to build the model and then simulate and derive the future information on that. As an opposite of AI where we are trying to achieve strong property, with the anticipation we are trying to achieve weak property. In the both cases we are usually satisfied with the other property (weak for artificial Intelligence and strong for anticipation).

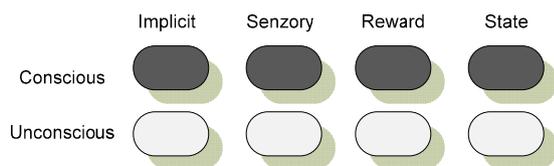
### **Conclusion of Weak and Strong Properties**

Despite the same terminology, the understandings of weak and strong properties are different in the research

areas of ALife and anticipation, making it harder to realize the links and consequences. Our approach is definitely a *weak AI approach* while we are trying to achieve the *weak anticipation*. The reactive anticipation does not create any model to reason hence it uses the strong anticipation. Our goal is to design and build a *multi-level anticipatory creature*, which should definitely exhibit the weak anticipatory property.

## MULTI-LEVEL ANTICIPATION

It is obvious that there seem to be several types of anticipation as shown above. Even though we embrace the categorization of Butz anticipation (Butz et al. 2003) we were not entirely satisfied with it. As shown in the examples we struggle to categorize his 4 types from the point of control of the creature's will. We solved this by applying *each category on conscious and unconscious level*, creating thus 8 types of anticipation, which we call multi-level anticipation, or *8-factor anticipation*. This is an original and novel contribution to the theory of anticipation that we came up with and will further develop and research. All the levels are schematically shown on Figures 1.



Figures 1: All Eight Levels of Anticipation.

There are these sorts of Anticipation: *Unconscious Implicit*, *Conscious Implicit*, *Unconscious Sensors*, *Conscious Sensors*, *Unconscious Reward*, *Conscious Reward*, *Unconscious State*, and *Conscious State*

We can say that the complexity grows in the picture from the left to the right and from the bottom to the top. In this article we focus on the first two levels only. One approach or architecture spans through multiple levels usually. First we will describe our understanding of both levels, then we will present an explanatory experiment we conducted to further demonstrate the ideas. To compare the work with other and statistically evaluate, we would need to encompass more than these two levels. (See CONCLUSION.)

### Unconscious Implicit Anticipation

Under unconscious implicit anticipation we understand the behaviour that was imprinted in a creature by Nature (evolution) or creator (in artificial case) and that is not voluntary. Reactions and reactive behaviours itself are not anticipatory. It is very often used and wrong understood as an opposite of anticipation. So what exactly are reactions with anticipation (reactive anticipation)? We cannot say that the reaction is associated with prediction of next sensory value, reward or even state because these are not available. We are

here at the first and basic level of our multi level anticipatory model and thus there are no means to evaluate a reward or a state. Classical view of implicit anticipation would be satisfied with the fact that it is the prerequisite given to the system either by the long evolution or by the creative mind of architecture designer (Nahodil et al. 2004).

The creature has only the set of *inputs I* and set of possible *outputs O* available (at this very basic level). Let's assume discrete values, which we typically have in a virtual environment. We are not speaking about *agent sensory inputs* or *actions* yet; we intentionally used *inputs* and *outputs* instead. The reason for this is an attempt to generalize this description so it can be used for agent's internal blocks and not only for agent as whole. The reaction base is typically in form of projection  $I \Rightarrow O$ . The inference mechanism is simple. If any of the input matches, the *output* is executed.

This approach was used by Brooks on MIT round about 1986. There is couple of possibilities for a technical realization from *binary rule base* (Brooks approach) to *ACS - Anticipatory Classifier Systems* (Butz 2002). Let's continue with the formalism. The anticipatory approach would expect another input after the executed action  $I \Rightarrow O \times I$ . Up till this point this is well known and documented. But on unconscious implicit anticipation there is no mechanism to modify this rule base, other than evolution or redesign. At this level we do not need to solve creation of new or forgetting of obsolete rules here, because the rule base is fixed and it is subject to evolutionary changes only. It seems there are not many options, but *in simplicity is power*. We would like to point out *two possible modifications*, which we also consider *as original ideas*. The first will be described right away, the second will be discussed in the next chapter, and both will be shown in the examples in the *Implicit Anticipation Model* part. One to add to the expectation also expected next action. This is expected to improve the reaction time. It will result in the projection of  $I \times O \Rightarrow O^2 \times I$ . This describes the expected or better said "prepared" next action. Let's take an example to demonstrate the idea. Imagine the predator evasion situation. One agent is equipped with standard prediction scheme, and second with the modified one as suggested above. Both are in the vicinity of predator (*input I*) the reaction of both is to flee (*output O*). Even if the reaction process is fast it takes some time. Let us analyse what happened in case the original agent needs to take another decision. It has to go through the *action selection process* again to derive new action (even if the new action is the same as previous one). On the contrary if this moment comes to our modified agent it can straight away execute the prepared action.

Except the basic reaction base, another area of involving the implicit and unconscious anticipation is the *inner agent* processes, which imitate the creature physiology, energy management, and other internal

processes. The inner process can either directly or indirectly influence the decision process. If it influences the decision indirectly then it needs some regulation system (once again take the example with the blood pressure). This regulation system is hardcoded within the organism and is not consciously controlled hence it can be classified as implicit unconscious anticipation. The specific implementation of this category can be done via coded *input output base* with an association mechanism. There are of course several possibilities how to code the rule base and the mechanism, but this area is well researched for many years, so we will just build on the existing approaches.

### Conscious Implicit Anticipation

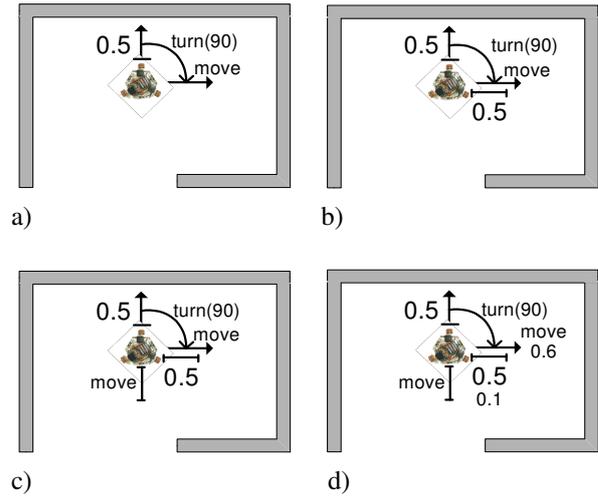
The combination may seem illogical at first glance, because of what we have said about implicit anticipation above. It is *something imprinted in the creature* by design. How this can be consciously controlled? The explanation is simple, here still everything depends on the design, but the results are consciously processed or can be chosen to be consciously controlled. This means that inputs of other blocks, such as desired state, are available as inputs for this block. In order to create a new non-atomic action, we can chain the existing actions together, which would have no decision time in between and we can also focus the attention. That is important aspect of behaviour and it can be controlled on this level of our design, even though the higher level can control it too. Our point here is that even if the animal or agent executes the reactive behaviour, it needs to have a focus on something initially.

We will continue here with the formalism we started above. Even here we still have only the set of *inputs I* and set of possible *outputs O*. We can use everything from the previous level up to the next *output prediction*  $I \times O \Rightarrow O^2 \times I$ . At this point, because it is conscious part, we will introduce the second suggested improvement to the rule base scheme. We do not have the reward yet, but we can have a rate of change for the *input* value. In the ALife, the *output values* have typically discrete values often not expressed by numbers (action for example). In case of the *output* some statistical measure such as probability or likelihood it is appropriate. This is another parameter that can bring value to the decision process and help to choose the optimal action. This describes the typical scenario, but in fact any combination in term of discrete and continuous of the *input* or *output* can occur. So we are adding two new values the *ri* and the *ro*, which we will call *rateability* (combination of words rate and probability). This enriches our rule equation so we get  $I \times O \Rightarrow O^2 \times I \times \mathbb{R}^2$ . For continuous or discrete values that are differentiable we can use the rate (first derivation /difference providing the speed of change). For the non-differentiable values we can use probability of their occurrence counted during the agent lifetime to

compute the *rateability*. Obtaining these values is not an original idea standalone, but we believe it is new in context of anticipatory behaviour.

### Implicit Anticipation Model

We will summarize and illustrate here what was described in the previous two subheadings. We will also compare these to the classical approaches and show that even though what we described seems to be basic and simple the amount of information varies significantly.



Figures 2: The four possible options of available data in the same situation: a) the classical reactive approach, b) the classical anticipatory approach, c) first suggested improvement - action anticipation, d) second suggested improvement - rateability evaluation

As mentioned the situations on the Figure 2 are described below with examples reflecting the respective values. The points a. and b. show *current approaches*, the points c. and d. show the *approaches that we suggest use*.

#### a) The classical reactive approach

IF  $x$  THEN  $y$  where  $x \in I, y \in O$  (1)

Example: IF distance < 0.5 THEN turn(90)

#### b) The classical anticipatory approach

IF  $x$  THEN  $y$  EXPECT  $z$  where  $x, z \in I, y \in O$  (2)

Example: IF distance < 0.5 THEN turn(90) EXPECT distance  $\geq 0.5$

#### c) First suggested improvement - action anticipation

IF  $x$  AND PREVIOUS\_ACTION  $a$   
THEN  $y$  EXPECT  $z$  AND EXPECT\_ACTION  $b$   
where  $x, z \in I, y, a, b \in O$  (3)

Example: IF distance < 0.5 AND PREVIOUS\_ACTION move THEN turn(90) EXPECT distance  $\geq 0.5$  AND EXPECT\_ACTION move

d) **Second suggested improvement – rateability evaluation**

IF  $x$  AND PREVIOUS\_ACTION  $a$   
 THEN  $y$  EXPECT  $z$  AND EXPECT\_ACTION  $b$   
 WITH  $\langle r_i, r_o \rangle$

where  $x, z \in I, y, a, b \in O, r_i, r_o \in \mathfrak{R}$  (4)

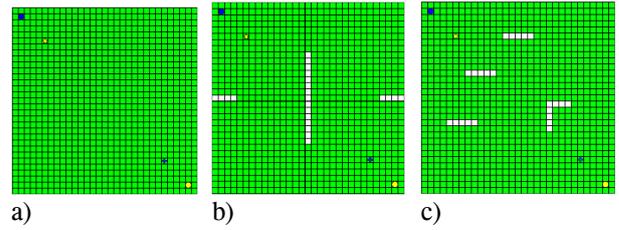
*Example* IF distance  $< 0.5$  AND PREVIOUS\_ACTION move THEN turn(90) EXPECT distance  $\geq 0.5$  AND EXPECT\_ACTION move WITH  $\langle 0.1, 0.6 \rangle$

So far we have described what we understand under these two layers of our design. It is due to describe how to achieve this, what algorithms, approaches and techniques are used. So we need to address how the inference, storing the rules, recalling them, forgetting and matching the input on the sensors to the rules will be done. We have several options here, but we still cannot use any of the successful approaches like Reinforced Learning (RL) or ACS at this level because these consider reward or outcome and these are not available on the presented two levels yet. Two things will be taken under consideration here. One, the above described two blocks are part of a larger architecture and they will certainly interact with other blocks. So we can, on the premise of having other blocks, use ACS and say that it will not only implement the two levels described but others. Second thing is that our goal is to provide a self-sufficient architecture for each level not only for testing and experiments purposes but also for interoperability. This means that we still need a support mechanism for this to make it work. At the second discussed level the animate should be in conscious control and hence the desired value should be available (even when produced by higher levels). We use (for the technical implementation) the *emotivector* introduced by Carlos Martinho (Martinho 2007). We have selected the emotivector for its simple yet effective way of implementing the attention focus.

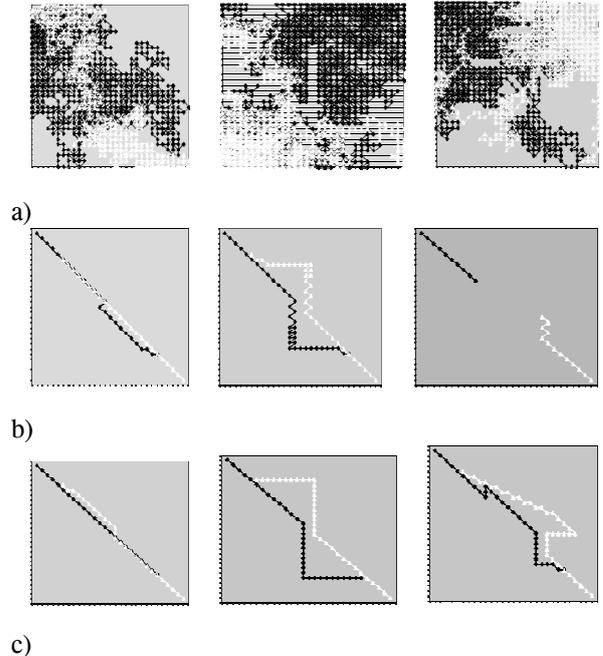
## EXPERIMENTS AND OBTAINED RESULTS

We would like to demonstrate the above suggested approach on experiments conducted namely with the *unconscious implicit anticipation*. Simulations in the virtual environment are the methods (for ALife in most cases) how to test theories and compare effectiveness of results with others. We have conducted our experiments in the REPAST simulation tool (REPAST 2009).

The setup of the experiment is placing an agent (robot) into a simulated world with several objects. There are walls obstructing way here and the beverage, which the agent has to reach. The goal for the agent architecture is to reach the target in effective manner. We focus on showing the *unconscious implicit anticipation effects* to demonstrate our new proposal in more details. There are 3 layouts of the environment on Figures 3. There are always two agents in each simulation, each trying to reach different goal location.



Figures 3: The three layouts of the environment  
 a) one without obstacles, b), c) two with different types of obstacles.



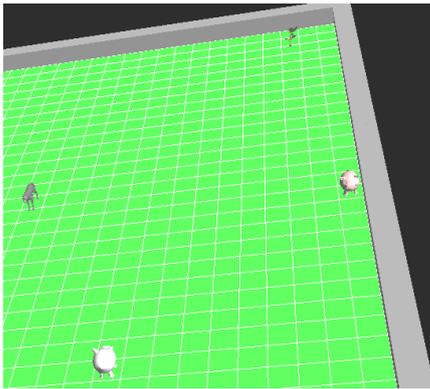
Figures 4: The performed experiments on the top the layouts of the environment. In the rows results with different decision control mechanism a) random movement b) unconscious implicit anticipation behaviour c) implicit anticipation behaviour based on “wall following”.

The objectives of this experiment are very simple. We are trying to show here the meaning and differences in the implicit anticipation. The setup of the experiment is three different obstacle scenarios with two agents, each trying to reach food. In the first experiment b), the unconscious implicit anticipation of “right angles” was used, which means that when meeting the obstacle rotating by 90 degrees is expected to overcome it. We can see that in this case the 3rd scenario is not achievable (agent get stuck, or oscillate between two positions). In this example the simple imprinted mechanism fails, due to incorrect anticipation. In the third experiment, we used different mechanism “wall following”; hence we anticipate continuing by the wall and not changing direction too often. This architecture can successfully complete the third scenario. What was shown here is the *unconscious implicit anticipation*, as we understand it, the different behaviour patterns could be either designed or evolved.

With the *conscious implicit anticipation* two experiments were conducted. The first experiment was

devoted to the selection of the best predictor for the *emotivector*. Two possibilities were evaluated by *Simple Predictor* (SP) and by *Limited Simple Predictor* (LSP). LSP uses the same equation, but also keeps *history of the input values*, calculates the mean and the deviation and *limits of the prediction* if outside the statistical range (they are described in detail in (Kohout and Nahodil 2007), (Elmahalawy and Nahodil 2007b)).

The Simple Predictor convergence speed was slow (convergence to  $0.1 \pm 0.01$  was in 87 steps) while the other predictor was able to converge in 5 steps. These obtained values are then further processed. However the properties of predictor play the key role in the overall design. The other experiment was designed to test the *attention focus mechanism*. In this scenario there were two static agents and two moving agents. One static agent was an observer evaluating the environment input and focusing attention (shown as wolf), the second agent was a non-moving agent (shown as flower). The second two agents (shown as pigs) had different moving patterns. One agent was running in circles and second one was moving randomly the scenario. This simulation is shown on Figures 5 below.



Figures 5. Attention focus mechanism - the 3D model.

The *moving agents are much more interesting for the observing agent than the static ones*. This static agent was expected based on the fact, that *emotivector* is sensitive to the observed value change in time. This reveals the strong and the weak sides. For the attention focus, the changes in the environment are relevant only on this level. This is acceptable on the *basic "reactive"* level.

## CONCLUSION

In this paper we have focused on the *topic of reactive anticipation*. We have shown that the reactive behaviour employs anticipation inherited by the creator (nature, designer) and we demonstrated the *effect of the implicit anticipation on behaviour* on many experiments. These experiments have brought a new light into the anticipation research. These are however basics for our *multi level anticipatory approach*. This approach was not yet proven to be significantly better than other works here due to the limitation of this paper

to only the first two levels. The goal was to describe basics of our novelty approach to encompass *the consciousness in the anticipation*. This is a potent topic, and we tried to prove that in behaviour based robotics. This paper also includes a short discussion about weak and strong properties in areas of AI, ALife and Anticipation. The conclusion is that *AI and ALife current definitions are hard to relate to the anticipatory ones*. Authors believe that this paper could be a good starting point for further research.

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**KAREL KOHOUT** obtained his first - EE MSc. degree in Technical Cybernetics also from the Czech Technical University in Prague, Dept. of Cybernetics in 2006. He is still a PhD student at the same Department of Cybernetics, finishing his PhD theses under supervising of Pavel Nahodil now. He has taken active part on many international conferences. He is also (co-) author of more than 20 published papers in topic of behaviour based control and simulations in Artificial Life Domain mainly.

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